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INVESTIGATION TO DEVELOP A MULTISTAGE FOREST SAMPLING INVENTORY SYSTEM USING ERTS-1 IMAGERY

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16. Abstract This investigation examined the applicability of ERTS MSS digital data in increasing the precision of timber volume estimates in multistage sampling designs. In the designs considered, sampling units are as small as one square mile as defined by the General Land Office Cadastral Survey of the United States. A precision annotation system was developed for delineating the sample unit corners on U2 aerial photographs, ERTS MSS images, and MSS digital tapes. The RMSE of corner location was about 200 meters in the MSS coordinate system. A digital interpretation model was devised for predicting timber volumes by sample unit from the MSS digital tapes. The model utilizes Butler's field strength approach to non-supervised clustering and regression analysis. The MSS interpretive model proved to be highly significant in the cases tried, but the gains in sampling precision achieved varied from zero to 50 percent depending on the sampling method and the population to which the methods were applied. Of the methods tried, regression sampling was most robust. The best single variable in the interpretive model was the difference between MSS bands 5 and 7, while the contrast variable contributed little to the overall gain.

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PREFACE

Objectives. This ERTS investigation had three main objectives. These were (1) to investigate the applicability of ERTS data for improving the precision of multistage forest inventories, (2) to develop a precision analytical annotation technique so that sample units as small as one mile square could be reliably located on ERTS MSS images as well as in the coordinate system of the digital tapes, and (3) to develop an interpretive model capable of deriving forest related variables from the MSS digital tapes.

Background. The first application of multistage sampling using space and aerial photography to forest surveys was conducted with data obtained by the Apollo 9 astronauts in 1969 (Langley, et al., 1969). While lower altitude aerial photography had been used in forest surveys for many years, the advent of high-altitude aircraft and spacecraft generated an interest in the application of small-scale imagery to these surveys. While the Apollo 9 experiment demonstrated that space imagery could provide data to improve the precision of forest surveys, it remained to be determined if (1) the methods could be applied to sample units prespecified on the ground, (2) computer-oriented interpretation techniques could be applied to space data for advantageous use in forest surveys, and (3) the particular sampling design used had any significant effect on the gain in precision and stability of the forest estimates. These questions were addressed in the present study.

Scope. The test site used in this investigation was the aggregation of lands owned by the Southern Pacific Land Company in Trinity County, California.

The types of sampling modes that were compared for relative gains in precision were stratified, ratio, variable probability, and regression. Within these, various combinations of stages were tried including (1) space, high-altitude aerial and ground data, (2) space and lower altitude aerial and ground data, (3) space and ground data, and (4) aerial and ground data.

The precision image annotation system that was developed included the general capability of annotating the corners of sample units within the geometry of aerial photographs, ERTS MSS imagery and ERTS MSS data tapes. Image overlays were produced by computer methods for visually identifying the sample unit corners on each of the image types. Concurrently, the coordinates of the points in the computer tape system were determined. Hence, specific sample units could be addressed in the the computer for interpretation purposes. The annotation system is capable of correcting for image distortions caused by earth curvature, terrain relief, and systematic distortions in the MSS.

The MSS analytical interpretation system consists of a data handling subsystem, an unsupervised clustering algorithm based on Butler's vector field approach, a sample unit overlay subsystem, and a regression model for relating classification data to continuous timber volume data. The system also includes a variable generating subsystem to formulate variables for use in the interpretation model from multispectral data. Spatial relationships, such as contrast, are investigated by means of the Hadamard transform operating on 2^n square matrices of MSS pixels where the feasible values of n appear to be positive integers less than eight.

Results. The main results of the investigation can be summarized as follows:

1. The annotation system produced a RMSE of about 200 meters ground distance in the MSS data system with the control data used. This indicates that, with care, sample units as small as one mile square can be isolated for analysis.

2. All the analytical MSS interpretation models tried were highly significant. However, the gains in forest sampling efficiency that can be achieved (compared to multistage sampling with equal probabilities at the first stage) by using the models vary from zero to over 50% depending on the area to which they are applied and the sampling method used. As anticipated, the greatest gains are achieved where the survey area encompasses the model training area. The gains decrease as the training area is enlarged or if the models are applied in new areas outside the training area. In these situations, we encountered gains of about 10 to 15 percent only.

3. Among the sampling methods tried, regression sampling yielded substantial and the most consistent gains. Variable probability sampling is apparently capable of achieving greater gains than regression sampling, but carries higher risks. For example, extreme outliers can be very bothersome if even one sample unit is grossly misinterpreted or if the image characteristics do not relate well to ground conditions.

4. The single most significant variable in the interpretation model was the difference between bands 5 and 7.

5. The contrast variable, computed by means of the Hadamard Transform was significant but did not contribute much to the interpretation model.

6. Forest areas containing very large timber volumes because of large tree sizes were not separable from areas of similar crown cover but containing smaller trees by means of ERTS image interpretation only.

7. All correlations between space derived timber volume predictions and estimates obtained from aerial and ground sampling were relatively low but significant and stable. Hence, the MSS data should consistently improve the precision of forest surveys with given sample sizes if used carefully and appropriately.

8. There was a much stronger relationship between variables derived from MSS and U2 data than between U2 and ground data. Therefore, better models should be developed for interpreting U2 type data if they are to be a key link in multistage designs.

Recommendations. Recommendations for a continued research effort fall into two categories: (1) those related to improving the present models and techniques for use under the conditions presented in this report; and (2) those related to a much broader application of ERTS MSS imagery and U2 high-flight imagery in multistage forest inventories on a larger scale under a variety of conditions.

Some recommendations of the first category are the following. The digital interpretation system developed in this investigation can be greatly improved upon. Two areas for possible improvement are visualized: (1) the intel size of 8x8 pixels is probably too large for best interpretation results; and (2) system performance can probably be enhanced by switching to a 4x4 or a 2x2 intel size.

In our work with the MSS digital data, the distinction between water and dark north facing slopes containing high timber volumes was a precarious one. The decline in gain experienced from training to test area may partly be due to a subtle shift between these tone signatures. Additional research would be necessary to remedy this situation. In this regard, we were handicapped by having only October imagery with a relatively low sun angle available for use at the appropriate time.

The U2 human interpretation model could be improved and stabilized over larger areas by using more than one photo interpreter. Several interpreters could mutually verify their interpretation standards as the interpretation progresses. Individual interpretations could then be averaged to provide more consistent estimates.

Perhaps one of the most important questions of multistage forest inventory has not been dealt with in this research. We investigated the interpretation models in terms of two stage combinations. However, we did not attempt to define optimal combinations of several models, sampling methods, and multiple stages simultaneously. When considering multistage inventory, one must be concerned with multiple combinations of interpretation models and sampling methods. Therefore, further research in these areas, as well as in applying the techniques in the other forest areas of the Unites States, would be appropriate.

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1.0 INTRODUCTION

1.1 Report Organization

This final report describes the Earth Resources Technology Satellite (ERTS-1) investigation concerning the development of a multistage forest inventory system. Such a system uses aerial and space platform imagery as well as ground data in a sampling framework through which timber volume estimates are obtained. The main objective of the investigation was to evaluate the usefulness of ERTS-1 imagery for the space platform stage of the inventory. A minor objective was to test and develop new techniques to make optimum use of available remote sensing information not only at the space level, but also at the subsequent aircraft levels.

This final report describes the techniques and methods tested during the course of the investigation and summarizes their significance for use in multistage surveys.

The background and the objectives for the investigation are presented in the introduction to the report (section 1.0). The main body consists of four parts. In the first part (section 2.0) we describe the image annotation techniques used for the investigation. In the second and third parts (sections 3.0 and 4.0) we report on the human and machine interpretation methods and models developed during the course of the research. In the fourth part (section 5.0) we evaluate the merit of the models and systems when used in a sampling survey context.

In the final section (6.0) we summarize and evaluate the work performed and the results obtained; and we present our recommendation for future research and the application of ERTS imagery in multistage forest surveys.

1.2 Background

The concept of multistage sampling as applied to forest inventory (Langley, 1969) can be summarized as follows. It is a method in which the selection of sample units at stage n+1 are based on criteria evaluated from the sample units at stage n. With n increasing, the total ground area sampled decreases until in the final stage a number of sample units is visited on the ground. At the same time, the expense incurred in the evaluation of a unit usually increases with n. For a forest inventory the extreme stages could be the complete evaluation of a unit on the ground on one hand, and the separation of land into forest and non-forest classes on space imagery on the other. Intermediate stages consisting of aerial imagery are used to provide a correlation chain through which the first and the last stage are connected. The precision of the survey depends on the quality of the links.

For a multistage inventory, improvement of this quality can be made with regard to the following three aspects of the inventory:

A. Alternative sampling designs should be evaluated to make optimum use of the relationships between variables extracted from the imagery at adjacent levels. It is

well known that in variable probability sampling the relationship between these variables should be a straight line through the origin to obtain maximum precision. In regression sampling this is not a strict requirement.

B. There must be spatial correspondence between sample units on adjacent stages of aerial or space imagery. To our knowledge no research has yet been performed to establish the sensitivity of the sampling variance in relation to spatial mismatches between sample units at different stages. However, by using a precision image annotation process, mismatches can be minimized leaving fewer and more important issues for investigation.

C. Relevant information must be extracted from the imagery. The greatest overall gain can be obtained in this area in terms of both accuracy and efficiency. One problem with the use of high-altitude space and aerial imagery for forest inventories has been that the traditional photo interpretation techniques based on crown closure and crown cover are not applicable at these altitudes. However, information on the distribution of forest and other vegetative types is definitely present, but has to be extracted with novel techniques in the framework of the multistage inventory. With the advent of ERTS,

superior multispectral space imagery has become available, and the evaluation of the usefulness of this imagery was the major objective of the present investigation.

Corresponding to the above three main areas for improvement of multistage forest inventories, our research proposal was divided into three main tasks, each with an ERTS component as well as containing proposed methods for improved use of aerial imagery.

Task I: Sampling design formulation relates heavily to the final use of the developed techniques in a sample survey situation and is reported on in the last part of this report, section 5.0.

Task II: Sample unit annotation on aerial and space imagery was logically the first task to be carried out, since one needs to know the location of the sample units on the imagery before any interpretation can be attempted. Sample unit annotation methods were developed for high-altitude aerial and ERTS multispectral scanner (MSS) imagery.

Task III: Development of interpretation methods was carried out during the second half of the project period, partially in conjunction with Task I, since each model was tested for its usefulness as soon as it was developed. An evaluation of the models in a realistic sample survey context, as required for Task I, formed the conclusion of the project. The

main sections in this report, 2.0, 3.0 plus 4.0 and 5.0 correspond to Tasks II, III, and I of the proposal, respectively.

1.3 Objectives

Task I: To test and evaluate, in a multistage sample survey context, the usefulness of ERTS MSS imagery in obtaining timber volume estimates of coniferous forests in California. More specifically, the broad objective is to evaluate the gain in sampling precision that can be obtained with a given sample size by introducing ERTS data at the first stage of a multistage sampling plan.

Task II: The main objective of Task II was to develop a precision sample unit annotation process for the U2 and ERTS images. Part of this task was to investigate the accuracies with which points could be located on the U2 and ERTS imagery by means of modified analytic photogrammetric techniques. These accuracies indicate the minimum sample unit size that can be used with ERTS MSS imagery.

A recent application of the multistage inventory concept to commercial property in the State of California demonstrated the need for the annotation of ownership patterns on aerial imagery. In this instance, clusters of General Land Office (GLO) sections proved to be natural sample units for this kind of forest inventory. Unfortunately, an approximately one-square-mile land unit is by no

means square on the map due to early primitive surveying techniques. In addition, the section is sometimes rather heavily subdivided.

The annotation problem for the commercial survey in which the first stage consisted of 1:40,000 scale aerial photography was solved by performing an individual resection for each photograph, followed by a prospective projection of all the relevant corner points of the land sections onto the photographs. In the ERTS-1 investigation we considered two additional stages; namely, a high-altitude stage of U2 RC-10 photography, and a space platform stage from ERTS MSS imagery. Thus, we were faced with the problem of also having to identify the land sections or multiples thereof as well as county lines and management unit boundaries on the U2 photographs and the ERTS images.

Task III: Our objective for the image interpretation research was to develop interpretation techniques and models of the following types: (a) human interpretation of small-scale U2 high-flight and ERTS space images; (b) machine interpretation of 1:40,000 scale photographs using a television-type image analyzing computer; and (c) digital interpretation of computer-compatible ERTS tapes provided by NASA.

The main thrust of the interpretation work was to provide and test a machine interpretation system for the MSS digital data. More emphasis was placed on this type of work than on other interpretation methods in view of the fact that human recognition of objects

decreases with decreasing resolution. Hence at the space level, machines can possibly perform a better and more consistent interpretation of tones and textures not directly related to the human experience.

2.0 IMAGE ANNOTATION

2.1 Introduction

The development of a subsystem to locate sample unit boundaries on the various stages of aerial and space imagery was an integral part of our investigation to develop a set of models and techniques for use in multistage forest inventory. The necessity for such a subsystem was demonstrated by the requirement for forest inventories of lands with irregular ownership patterns. These patterns defied the approach used in the early multistage inventory trials in which Apollo 9 photography was used (Langley, et al, 1969). At that time the sample units were simply defined by superimposing a uniform grid on the satellite image. Thus, to obtain greater spatial correspondence between the sample units of the various stages and to ensure that the inventory would be conducted within the property boundaries, we developed a computational method for transferring basic sample units from ownership maps to ERTS and U2 imagery.

Also of interest was the accuracy with which a single point could be located on the ERTS images so that we would know the minimum size sample unit that could be used at the ERTS stage of a multistage resource inventory.

2.2 Approach

The common approach taken for all three kinds of imagery used in the investigation was to perform an analytical resection for each individual image. The input to such a resection consists of

the image coordinates and ground coordinates of a set of identified points. The spatial location of the image center and the orientation of the image are the outputs of the procedure.

With estimates of these parameters in hand, other points such as property corner points can be projected onto the images using analytical methods.

The modifications in input data, as well as input parameters, for each type of imagery and the corresponding manufacture of annotation overlays are discussed in the following sections.

2.3 Image Annotation of 1:40,000 Scale Aerial Photographs

In a previous forest inventory we had obtained good results with individual spatial resections of 1:40,000 scale aerial photographs. We had developed a production program with a semiautomatic quality control that could process a large number of aerial photographs. The input to this program were the coordinates of a set of photo points which had been identified on USGS topographic maps and put into digital form with a map digitizer, as well as the set of digitized points defining the property boundaries.

The computed results were plotted with a Hewlett-Packard 9100A plotter on transparent stable material. The resultant overlay was then joined with the aerial negative and a combined print made. An example of such an annotated print is shown in Figure 1.

2.4 Image Annotation of U2 RC-10 1:126,000 Scale Aerial Photographs

To annotate the U2 RC-10 1:126,000 scale high-flight photographs, we had the option to either find a set of individual ground control points for each photograph or to find ground control points for only a few points and then to extend this control by means of a block adjustment on the U2 photographs. The latter approach was taken for the following two reasons. First, a block adjustment would yield greater precision than using control points from USGS planimetric maps, and second we could obtain precise coordinates for points which could both be defined on the U2 photographs and the ERTS images.

Since it is somewhat difficult to identify map features on ERTS imagery in rugged, mountainous terrain, we set out to identify a set of natural landmarks on the U2 RC-10 photographs that could also be readily identified on the ERTS images. We then used the U2 photographs to determine the ground coordinates of these points by executing a block adjustment. This block adjustment also provided the control for the resections of the U2 photographs. This approach was thought more desirable for the U2 stage because of its inherent greater accuracy due to simultaneous adjustments and the use of a precision MANN TA1/P monocomparator.

To minimize the programming effort, ground coordinates determined with the block adjustment, together with their measured plate coordinates, were fed into the existing resection program to perform the final transformation of the digitized section corners for the U2 stage.

2.4.1 Block Adjustment

The block adjustment was performed after the two strips of U2 photographs with ten photos each had been triangulated. Schuts triangulation and block adjustment programs were used for this purpose. Coordinates were expressed in a secant plane system, with its origin in the test areas, to remove the influence of earth curvature. The standard errors computed with the control points and tie points used in the adjustment proved to be 12.8, 10.3 and 4.4 m, respectively, for Easting, Northing and height. The planimetric errors correspond to a point identification error of about 0.1 mm on the photographic plate. The results can be considered very good in view of the 1:126,000 scale of the RC-10 photography.

2.4.2 Production of Image Overlays for U2 RC-10 Photographs

The production of image overlays with annotated sample units both for the U2 photographs and for the ERTS MSS images took place as indicated in the flow diagram of Figure 2 in which the differences between procedures for ERTS and U2 images are indicated by boxes labelled ERTS or U2.

Three types of points were annotated on the U2 and ERTS images. These were (1) the primary and secondary sample unit corner points, (2) the county line points and (3) the management unit boundary points. The units outlined on the U2 images

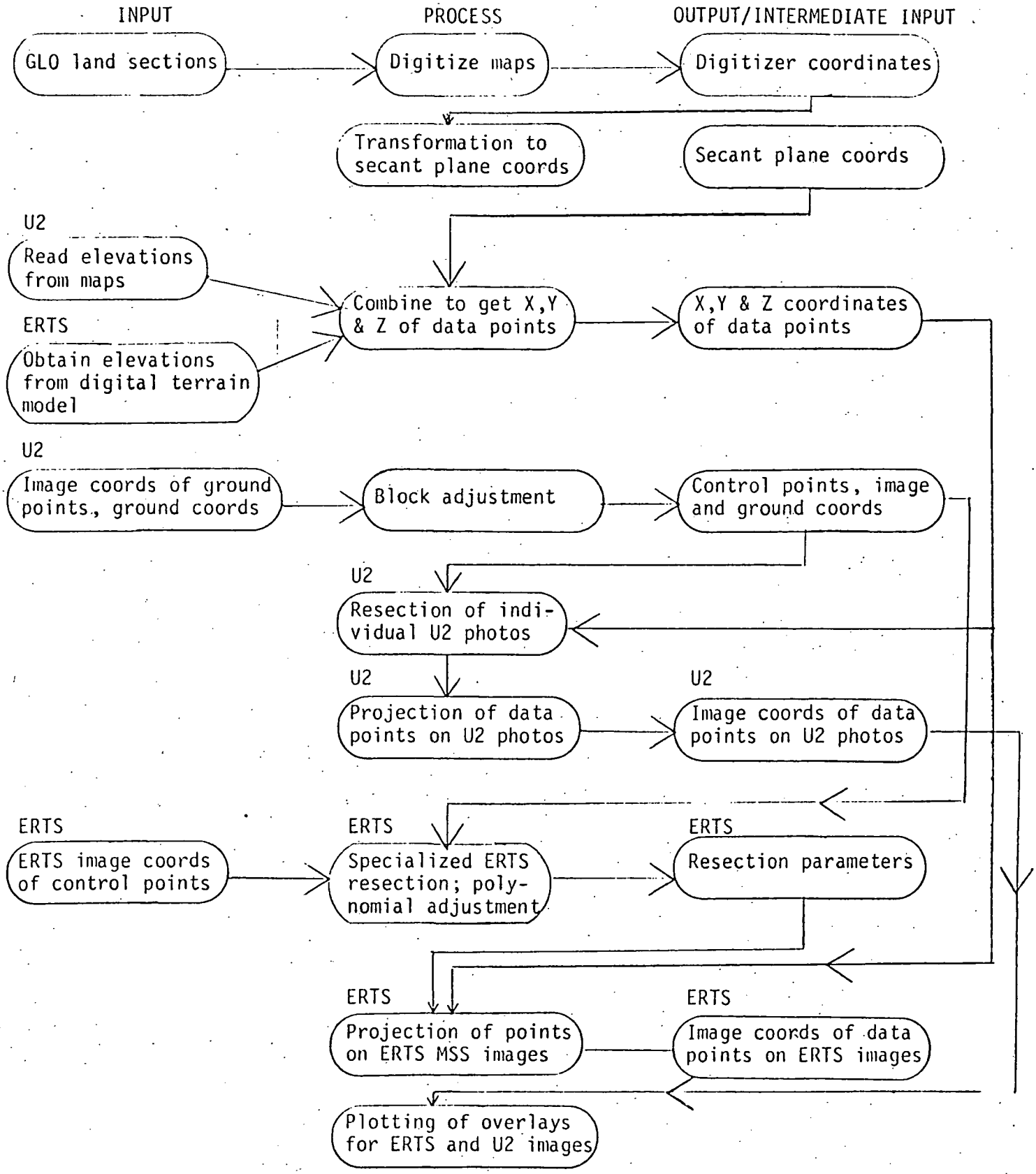


Figure 2. Flow diagram of ERTS MSS and U2 overlay manufacture.

were GLO land sections and fractions thereof. All points were digitized from 10 USGS maps at a scale of 1:62,500. Geographic coordinates were assigned to each digitized point by means of an interpolation method, using a set of map control points with known coordinates. The geographic coordinates were subsequently converted to secant plane coordinates. Elevations were read from the contour maps for all data points and were then added to the secant plane coordinates of the digitized points. Separate resections for the 20 U2 photographs were calculated using the control results from block adjustment. The data point coordinates were transformed to image coordinates by means of the resection results. The image coordinates were finally plotted on stable material templets using a Hewlett-Packard 9100A calculator plotter. An example of a U2 photo overlay is shown in Figure 3.

2.5 Image Annotation of ERTS MSS Images

2.5.1 Resection Theory

In contrast to the resectioning of aerial photographs, the ERTS MSS images present two problems: (a) the MSS image is produced by a multispectral scanner with a geometry different than that of aerial cameras, and (b) the imaging system has a very narrow perspective bundle.

The first problem is in part solved by the NASA data processing facility where the geometry of the MSS image is

partially shaped to resemble the geometry of an aerial photograph, not considering relief displacement, but taking into account earth curvature. The second problem causes an instability in the resection. It can be circumvented by enforcing some of the basic resection parameters, which must be determined from accurate outside sources such as the ephermeris data in the case of space images. We enforced the position of the simulated exposure station by assigning it the coordinates of the ERTS picture center.

To make the resection program for the annotation of the ERTS images completely general, so that it could be applied in other situations as well, we took the approach in which any parameter can be enforced at the value of its initial approximation by assigning appropriate weights. This approach can be implemented by using the parameter approximations in auxiliary equations in the linearized equation system:

$$\Delta p = p^{oo} - p^{o} + \varepsilon \qquad (1)$$

where:

Δp is the correction to the approximation at the ith iteration

p^{oo} is the approximation of the parameter value

p^{o} is the parameter estimate to be enforced in the solution, and

ε is the difference between the least squares adjusted value of the parameter and the value to be enforced in the solution.

For the first iteration, $p^{\circ\circ}$ is taken equal to p°. Then, if we place a large weight on the auxiliary equation, ϵ will be close to zero, Δp will also be close to zero, and the initial approximation, which is equal to the desired parameter value, will not receive any corrections in the iterative process. Thus, the initially assigned parameter value will remain unchanged throughout the solution.

The normal equations take on the following form for n data points:

$$\left(\underline{X}\,\underline{W}^{-1}\,\underline{X}'\right)^{-1}\,\Delta = \underline{X}\,\underline{W}^{-1}\,\underline{Y} \qquad (2)$$

with X' of the following form:

$$X'_{(11,9,n)} = \begin{bmatrix} a_x^1 & a_x^2 & \cdots\cdots & a_x^9 \\ a_y^1 & a_y^2 & \cdots\cdots & a_y^9 \\ 1 & 0 & \cdots\cdots & 0 \\ & & & \\ 0 & 1 & \cdots\cdots & 0 \\ \cdot & & & \cdot \\ \cdot & & & \cdot \\ \cdot & & & \cdot \\ 0 & \cdots\cdots & & 1 \end{bmatrix}$$

(the third dimension is not shown)

where a_x^1, a_x^2 ..., a_y^1 , a_y^2 are the partial derivatives of the collinearity equations with respect to the nine resection parameters for a particular point.

The matrix has the following elements (only the first row is shown):

$$\underset{(9xn)}{Y'} = \left[\varepsilon_x \; \varepsilon_y \; \left(p_1^{\circ\circ} - p_1^{\circ}\right) \; \left(p_2^{\circ\circ} - p_2^{\circ}\right) \; \ldots\ldots \; \left(p_g^{\circ\circ} - p_g^{\circ}\right)\right] \quad (3)$$

where ε_x and ε_y are the discrepancies resulting from an evaluation of the collinearity equations for the point under consideration with the current set of parameter approximations.

The matrix W is a diagonal 11x11 weight matrix with unit weights in the first two positions, zero weights for those parameters that need to be estimated, and large weights (for instance, 100 unit weights) for those parameters that are to remain constant.

Thus, with the indicated solution we were free to fix or estimate parameters as needed. As the orbital path of the ERTS satellite is known quite accurately, the likely parameters to be enforced in the solution are the exposure station coordinates for the center of the image. For this purpose, the indicated latitude and longitude of the photocenters were taken from the ERTS catalog. To obtain the satellite altitude we prepared a program that computes the exposure station coordinates from orbital data furnished by NASA, given the Greenwich Mean Time (GMT) pertaining to the image center. However, we anticipated that the latitude and longitude indicated in the catalog would be more accurate than the estimates computed by our program, since we only included first-order harmonic terms. In the solution, either the artificial focal length or the altitude needs to be enforced. We selected the altitude, since we

assumed that scale change would be introduced in the bulk process through the introduction of an artificial focal length.

2.5.2 Coordinate Systems

The same secant plane coordinate system used for the block adjustment of the U2 photographs was used for the resection of the ERTS MSS images. The conversion from the geographic coordinate system to the secant plane coordinate system yields coordinates of the control points in a cartesian coordinate system. The XY plane of this system slices through the reference ellipsoid, so that the point elevations also reflect earth curvature.

The earth curvature accounts for part of the perspective displacement encountered in the bulk processed MSS image so that the use of the collinearity equation for the along-track direction in conjunction with the secant plane elevations was, therefore, partly justified.

2.5.3 Polynomial Fitting of the Residuals

To eliminate systematic trends remaining in the point residuals after the resection had been performed, we included in the resection program a general polynomial fitting routine with which we could fit separate trend surfaces through the x and y residuals of the plate coordinates. This part of the program could then account for the unexplained remaining systematic distortions.

For the polynomial surface fitting we used hybrid orthogonal polynomials in the x and y plate coordinates, generated with a recurrence relation. The maximum power of the polynomials is automatically determined by the program and then discounted to evaluate all possible power surface fits. For each power, Root Mean Square Errors (RMSEs) were computed to assess the goodness of fit.

In the testing phase of the program we discovered that the polynomial fitting routine is general enough that, in terms of the residuals, almost identical results can be obtained by either performing a resection or by keeping all parameters fixed and then making the polynomial adjustment. Thus with the present program one can either opt for the classical resection technique or obtain the optimum polynomial fit.

2.5.4 Experimental Results

Two ERTS MSS images, designated 103 and 104, were resected. These frames covered our Redding (Northern California) test area. The ground control points were not distributed over the entire frames; rather, we confined them to those portions covering our forest inventory test site. In this regard, only 1/16 of image 103 was resected while the resection area for image 104 was approximately 1/6 of the total image area. A total of 18 points were used for image 103, while 30 points were used as input for the resection of image 104. In

both cases we only attempted to estimate the three rotation parameters and the artificial focal length in the resection. The other parameters were held fixed as described before. The estimated values for the rotation parameters (yaw, roll and pitch) were: -11.173°, -0.156°, -0.025°, and -10.984°, -0.161° and -0.019°, respectively, for images 103 and 104. To investigate the change in the rotation parameters and the exposure station coordinates in the case when the ground coordinates of the image center would be allowed to change, we removed the weights from the image center coordinates and obtained the following results: the image center shifted by approximately 7.2 and 35.3 km in Easting and Northing, respectively, while roll and pitch increased to 2.056° and 0.423°, respectively. The combined RMSE for x and y remained practically unchanged. This experiment reinforced the notion that shifts of the image center can be compensated for by rotational changes, causing an ambiguity when trying to estimate both types of parameters.

The quality of the resections of images 103 and 104 is indicated in the following table.

Table 1 -RMSEs FOR RESECTION OF MSS IMAGES 103 AND 104
(millimeters)
(x 1000: meters on the ground)

Image	Resection Result	After polynomial adjustment		
		Power 1	Power 2	Power 3
Image 103 (18 points)				
RMSE for x	0.142	0.129	0.123	--
RMSE for y	0.146	0.138	0.116	--
Resultant	0.144	0.133	0.119	--
Image 104 (30 points)				
RMSE for x	0.233	0.225	0.217	0.187
RMSE for y	0.196	0.181	0.176	0.146
Resultant	0.215	0.204	0.198	0.167

Firstly, we can see in Table 1 that the RMSEs vary from 0.119 to 0.233 mm. This variation ranges from one to two times the identification accuracy of the U2 RC-10 photography (0.1 mm), which is reasonable considering that the resolution of the MSS images in considerably less than that of the RC-10 photographs. Thus we can conclude that the point identification accuracy is the limiting factor with respect to the resection quality.

Secondly, we can see in Table 1 that the polynomial adjustment does not appreciably improve the RMSEs. To test this hypothesis we can compare the RMSEs before and after polynomial adjustment by combining them in the form of an F statistic. For instance, an F value of 1.29 can be computed from the resultant value after a third-degree adjustment (0.167). At the 90% confidence level this value should be greater than 1.51 to reject the hypothesis. This is not the case and thus we cannot confirm that the polynomial adjustment contributes significantly to the overall accuracy.

An interesting result of some further experimentation was that the polynomial adjustment is useful when, for instance, all the parameters but yaw (azimuth) are held fixed. In this case we would have to compare an RMSE of 0.575 with one of 0.199 after a third-degree polynomial adjustment, giving rise to an F statistic of 6.49. In this particular case a first-power adjustment (fitting of a plane) still gave an RMSE of

0.232 indicating that a scale change in the form of an adjustable focal length was the most important adjustment mechanism that was not allowed to function when held constant.

With the resection results in the form of the covariance matrix of the estimated parameters, it should be possible to propagate the variances to determine the accuracy of individual projected points. However, we know that the accuracy of an individual point is bounded by the RMSEs for x and y obtained from the resection. Thus, it seems reasonable to assume a maximum standard error of 220 meters on the ground for any point projected on the MSS image within the resection area. Had we only made a scale change and used the image directly as a map, the error would have been in the neighborhood of 743 meters according to the Data Users Handbook.

2.5.5 The Production of Image Overlays

After the resectioning of the space images was completed, the results were stored for subsequent use in the production of the image overlays. We decided to use the second-degree residual estimation in both cases even though the benefits of this estimation were not clear-cut, but we were convinced that the accuracy would not be degraded because of it.

Three types of points needed to be annotated on the space image, namely: the primary sample unit corners, the county line boundary points, and the management unit boundary points.

At the beginning of our investigation we decided to take 4x4 blocks of one-square-mile GLO land sections as the primary sampling units. Thus, one primary unit would cover approximately 16 square miles. All points were digitized from three maps at a scale of 1/2-inch to the mile. Geographic coordinates were then assigned to each point by means of an interpolation method using a set of map control points with known coordinates. The geographic coordinates were subsequently converted to secant plane coordinates. At this time no elevations had yet been assigned to the digitized map points.

To produce elevations for the digitized points we developed a digital terrain model of which a hypsocline chart is shown in Figure 4. This model covers an area of 125x125 km of our Redding test area and includes part of the Sacramento Valley, the Trinity Alps and the Mount Shasta area. In this area the maximum terrain variation is 14,000 ft. Elevations for the model were obtained by sampling an aeronautical chart with an 18x18 grid.

A test of the model showed that the RMSE of the actual terrain around the model surface amounted to 330 m. Under the assumption that the space image has a perspective geometry (including relief displacement), it can be shown that elevation errors in the order of 330 m would induce plate position errors of 37 micrometers, whereas errors of 111 micrometers would be incurred by assuming a mean terrain elevation.

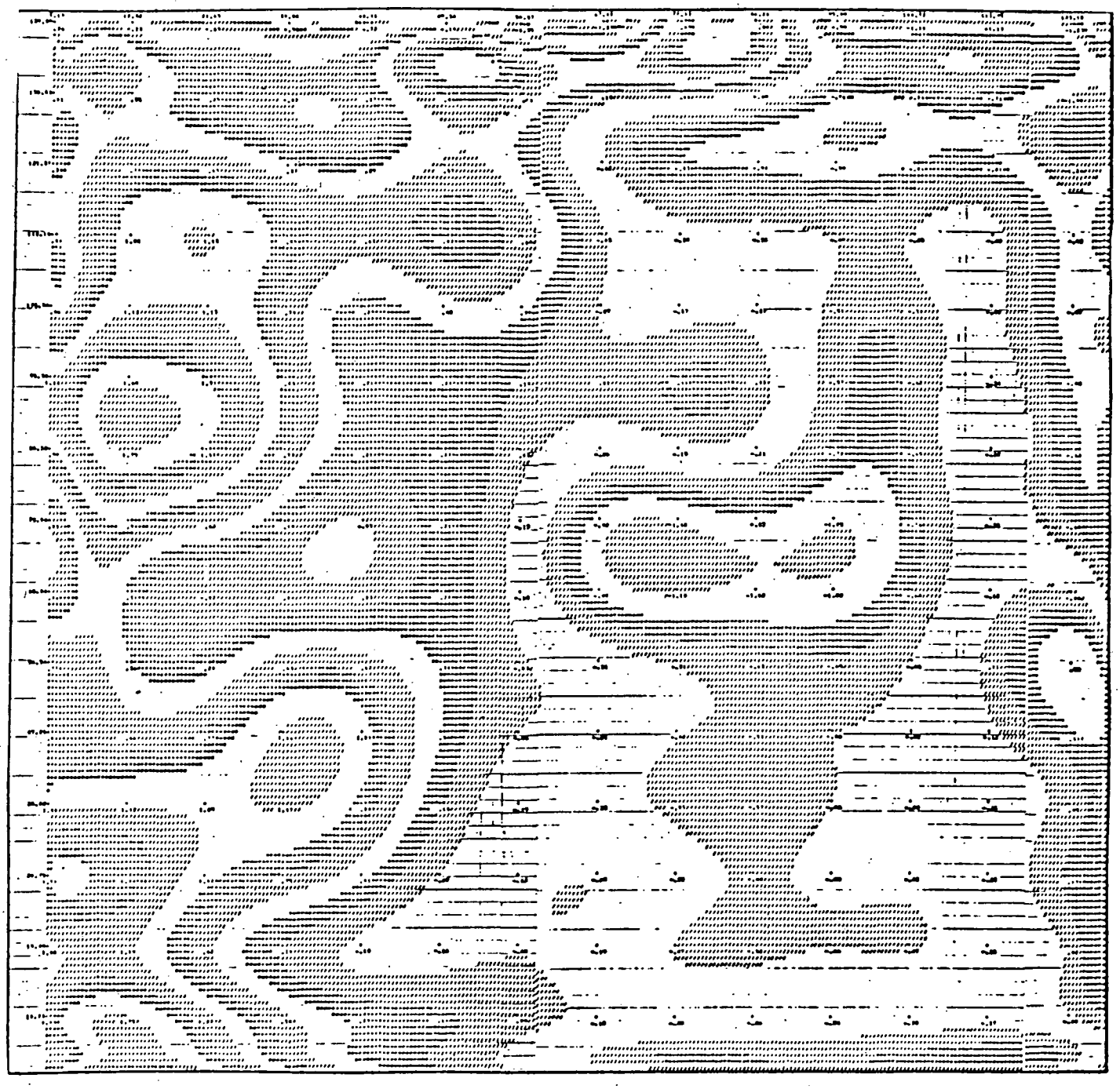


Figure 4. Hypsocline chart of Digital Terrain Model.

However, the MSS image is formed by perspective projection (including terrain relief) in the cross-track direction only, while in the along-track direction after bulk processing, the perspective projection would only be valid for general earth curvature. Thus, one would actually need two different terrain models to account for both types of perspective variation. At the present stage we used the one model shown in Figure 4, which accounts for both relief displacement and earth curvature since the elevations were transformed to the secant plane system.

After the elevations were assigned to the digitized points, they were processed through a program that sorts the points by frame number and projects them onto the MSS image in a rectangular coordinate system defined by the registration marks at the four corners. These coordinates were then plotted on stable transparent material with a Hewlett-Packard 9100A calculator-plotter at an enlargement ratio calculated by measuring a set of known distances on the enlargement.

At a later point in our investigation, after having performed several resections of ERTS MSS images, we concluded that there was sufficient geometric accuracy for the primary sampling unit to be as small as a one-square-mile GLO land section. Consequently, we used the point data base developed for the annotation of the U2 photographs and projected these section corner points onto the ERTS MSS images. An example of a 4x4 mile overlay produced with these points is shown in Figure 5.

As the main emphasis of our ERTS investigation was on digital processing rather than on human interpretation, the visual overlay was not the most important product of our annotation system. The set of digital property corner coordinates used to generate the overlay was more important, since it allowed us to process only those selected portions of the MSS digital data tapes which corresponded with desired one-square-mile land sections, or portions thereof.

As a significant result, we therefore obtained not only the capability to process a set of diverse and scattered sample units, but also to digitally process only those image portions corresponding to one ownership.

3.0 HUMAN INTERPRETATION MODELS

3.1 Introduction

In any multistage sampling scheme, measurements made on adjacent stages are tied together by models that provide estimates which can be related to the resource through sampling methods. For example, in variable probability sampling the model provides estimates which are used to determine selection probabilities for estimating a particular parameter at the next stage. In regression sampling, it is used to adjust inexpensive measurements made on one stage with the information obtained from the more expensive stage. In stratified sampling the model is used to define strata in which subsampling will take place.

Certainly the sampling method used is an important factor with regard to the overall level of precision obtained in the survey. But the interpretation model is of crucial importance since it governs the transfer of information from the image into the sampling design, and thus makes or breaks the quality of the survey.

In the remainder of this report we first describe the models and techniques that were developed; then we describe the methods with which they were tested and how they behaved in the test situation.

The types of interpretation techniques used fall into two categories: human interpretation and machine interpretation. Colwell (1965) observed that photo interpretation entails two kinds of operations: (a) observing such photo-image characteristics as size, shape, shadow, tone, texture, and location, and (b) judging

the significance of the features, based in large measure on their interrelationships or "association."

Colwell noted that while a machine may have the capability to do the former, rarely is it capable of doing the latter sufficiently well. On the other hand, while a human being excels at judging associations, he may not be able to do a consistent job of interpreting features such as tone and texture from large amounts of image data, as he is soon overcome by boredom and fatigue.

At the beginning of our investigation we were aware that image features most highly correlated with biomass volume would be the spatial distribution of tone and texture, and that large amounts of data would have to be interpreted. In addition, human interpretation would not be entirely capable of extracting the maximum amount of information from multi-channel images such as provided by the MSS system.

In view of these considerations, most of the human photo interpretation effort was concentrated on the U2 RC-10 high-flight photography. Photo interpreters were able to see individual trees on these photographs and they were able to associate their observations with ground experience obtained in the area. Even so, the interpretation process was sometimes difficult since it required a substantial amount of subjective judgement.

On the other hand, the ERTS interpretation effort became almost entirely machine oriented as photo interpreters were not

able to extract any kind of associative information related to biomass from the photographic ERTS images.

In the following section we relate our attempt to develop a suitable U2 RC-10 high-flight interpretation model for the prediction of timber volume.

3.2 The U2 RC-10 Timber Volume Prediction Model

As the basic unit of land to be used in the development of our interpretation model, we selected the one-square-mile GLO land section. These sections had been annotated on the U2 imagery, as described in Section 2.4. Specifically, we selected 40 sections to be used to develop and test a model. They were chosen to represent a wide range in timber volume in a variety of locations within our overall test site.

Our aim was to develop a regression type interpretation model for which the independent variables could be interpreted from the U2 photographs. This type of model would be more consistent, and less subjective, than a direct ocular estimation method. The dependent variable to be used was timber volume per square mile as known from the records of the Southern Pacific Land Company.

We started out with the interpretation of eight variables. These were (1) the percentage of a parcel on southern exposure; (2) the percentage of southern exposure covered with coniferous forest; (3) crown density of the conifer covered portion; (4) percentage of large trees on this portion; and the variables (5)

through (8) being a repeat of the first four variables for the northern exposure.

In this first interpretation experiment we interpreted black-and-white prints of the U2 color infrared photographs. Two interpreters estimated the 8 variables for the 40 sections twice. The initial idea was to average the four sets of interpreted data to reduce their variability and to reduce interpreter bias. For this purpose we did an analysis of variance to determine if there was a significant difference between interpreters, and to test the homogeneity of variance among the different data sets. The outcome of these tests showed that the data could be averaged. Special care was taken to make the data consistent by using the conference interpretation system, where common standards for the interpretation were continually established.

Using the averaged eight variables, we tried six different models incorporating linear and non-linear combinations of the variables. The outcomes did not differ significantly from model to model. The multiple correlation coefficient was in the order of 0.65 and the standard error of the estimate was of the magnitude of 2.5 million board feet (bd. ft.) per square mile. We discovered, however, that we could economize on the interpretation effort by averaging the variables for the northern and southern exposures, as this distinction apparently did not contribute to the overall result.

In the next experiment the number of variables was reduced to three; namely: (1) percentage of the section covered by coniferous forest (C); (2) crown cover density of the coniferous forest (D); and (3) the percentage of the stand in large trees (L).

In addition, we investigated two other factors; the difference between the use of black-and-white or color infrared photographs, and the difference between interpreters. The results of the second experiment in which we tried three models, two interpreters, and two kinds of photography are given in Table 2.

Table 2. RESULTS OF U2 RC-10 PHOTO INTERPRETATION EXPERIMENT

Model	Black-and-White		Color Infrared	
	Int. 1	Int. 2	Int. 1	Int. 2
	Multiple correlation coefficient			
1. $V=M+CD+CD^2+CL+CL^2$	0.71	-	0.74	0.64
2. $V=M+CD+CD^2$	0.58	-	0.58	0.53
3. $V=M+C\left(D+D^2+L+L^2\right)$	0.72	-	0.74	0.65

In Table 2 there are no entries for the second interpreter under black-and-white photography, since this interpreter was no longer available. However, it can be concluded from the color infrared interpretation that there was indeed a significant difference between interpreters.

The second conclusion that can be drawn from the experimental outcomes is that the difference between color infrared and black-and-white photography is very small, so that the type of photography used does not seem to be an important consideration in this case.

The variable percentage of large trees (L) was a source of complaint during the interpretation work. Highly subjective judgment was required for its interpretation. We, therefore, omitted this variable (model 2) to determine its influence on the multiple correlation coefficient. The decrease in this coefficient, however, indicated that the variable made an important contribution and, thus, it was included in the final model.

The third model was the final one selected for testing in a sample survey situation. In Section 5.3.2 we discuss how the various U2 RC-10 interpretation models can be used in four sampling schemes, and what their relative precision could be in each situation. The results of using the third model under simulated operational conditions are further described in Section 5.4.5.2.

4.0 MACHINE INTERPRETATION

4.1 Introduction

In the previous section we mentioned that the most suitable machine-oriented interpretation process is one in which basic tone and texture parameters are extracted from large amounts of image data without associative discrimination. Such a task creates boredom and fatique for the human interpreter, affecting the consistency of his interpretation. In addition, a machine could possibly be more efficient than a human interpreter.

We also mentioned that in the context of biomass interpretation an ERTS MSS image lends itself better to machine interpretation than human interpretation.

In the context of a multistage inventory, however, another type of imagery was considered for machine interpretation for the reason outlined above. That is, the interpretation of large-scale aerial photographs for a forest inventory requires tedious and laborious tree counting that could possibly be automated.

The section on machine interpretation is, therefore, divided into two parts. Firstly, we report briefly on our effort to eliminate tree counting on large-scale photographs by using a density slicing, particle analyzing machine. Secondly, we will report on our effort to develop a digital timber prediction system, using the MSS digital data tapes.

4.2 IMANCO Quantimet Machine Interpretation

For this investigation, 1:40,000 black-and-white infrared aerial photographs englarged to a scale of 1:24,000 were used. On

these images were located a set of 167 sample strips with a width of eight chains on the ground, all within Southern Pacific Land Company parcels in Trinity County; ground volume estimates were available for all 167 sample strips from a previous forest inventory.

Machine Configuration

Basically, the IMANCO Quantimet 720 is a density slicing machine also capable of counting and measuring the separated objects in the various grey levels. For the experiment the images were sliced such that the darkest level mostly represented tree shadows and north slopes. The next to darkest level consisted of dark vegetation, and the next to lightest level was composed of light vegetation. The lightest level mainly represented bare areas and brush.

In addition to density slicing, the machine has a capability for measuring areas of the features in the various slices. For this purpose eight area-size categories were selected ranging from one picture point to an 8x8 cell of picture points, where a picture point was approximately 2x2 mm.

Two other features of the IMANCO Quantimet are the capabilities to make intercept counts and end counts. With the intercept count, a horizontal chord intercepting the blob is counted whenever it satisfies the sizing criteria. In the end count, all the downward projections which fall within the frame to be analyzed are counted and can be grouped by size.

Modes of Operation

The IMANCO Quantimet is connected to a teletype with which selected variables can be recorded. For our experiment the following variables were selected for recording: (1) the total area in each slice, (2) intercept counts in each level by sizes, and (3) end counts in each level by sizes.

Analyses

Using the ground data from the Southern Pacific Land Company survey, regression models were formulated where the dependent variable was gross conifer timber volume obtained from other regressions based on tree counts obtained on the ground. The observations on the dependent variables were obtained from the IMANCO Quantimet.

The procedure used was to compute principal components of various combinations of variables both within and across density slices. Components were computed for the following configurations:

1. Across all variables within each slice.
2. Across intercept counts only within each slice.
3. Across end counts only within each slice.
4. Across end counts over all densities.
5. Across intercept counts over all densities.
6. Across area counts over all densities.
7. Over all variables combined.

After obtaining the principal components, correlation matrices were calculated to determine which principal components were most highly correlated to the dependent variable. After screening,

various combinations of principal components were formed from the eigen vectors and used as independent variables in regression models. The results were somewhat disappointing. Correlation coefficients between the dependent variable and the individual components ran as high as 0.34, but most were less than 0.20, with several in the 0.20 to 0.30 range. When combinations were tried, (multiple regressions) the highest multiple regression coefficient estimated was 0.55.

When outliers were successively removed from the data set, the correlations gradually rose to 0.76. However, so many outliers had to be removed to achieve this figure that we were simply trimming the tails of the distributions.

Our conclusion for the experiment was that the distribution of the dependent variable has too large a variance for the particular data set of IMANCO Quantimet variables to be useful in the cases tried. However, other projects which utilized large-scale 70mm photography indicated that measurements obtained from the Quantimet equalled those of human interpreters when correllated with timber volume measurements.

4.3 The Digital ERTS MSS Interpretation System

4.3.1 Introduction

The digital interpretation system was developed on the premise that a special system would be needed for the purpose of a multistage inventory. The characteristics of the problem

at hand requiring such a special system are: (1) the presence of extremely rough and mountainous terrain; (2) a continuously varying timber species mix with varying crown cover; (3) the need to estimate biomass in the form of timber volume; and (4) the required capability to interpret relatively small and accurately located sampling units with irregular ownership boundaries. These requirements are much different from the agricultural conditions that govern the characteristics of other digital classification systems.

The system described in this report is made up of three basic components: (1) an image handling subsystem; (2) a training subsystem in which all the parameters for the interpretation process are determined; and (3) a digital timber volume prediction subsystem that interprets the image to make the timber volume predictions on a land parcel basis.

The overall system is different from most other digital classification systems in that the final product does not consist of a discrete set of classes. Instead the results are estimates of a continuous variable: biomass in the form of timber volume. We therefore avoided using the term classification system in this final report. However, an important part of the training subsystem is a classification program. The classification at this stage is strictly an unsupervised clustering into land classes. These classes are then converted to percentages of areas occupied by the class in a given

parcel which are then regressed on a set of known timber volume estimates for a certain training area. The results are used to estimate timber volumes in other areas.

We describe the principles and operating procedures for the three subsystems in the following three sections.

4.3.2 The Image Handling System

The image handling system was designed to achieve the following objectives: (1) to locate sampling units in the digital data with sufficient accuracy; (2) to minimize tape handling and random access retrieval; and (3) to work with nxn matrices of pixels ("intels"), rather than on a pixel-by-pixel basis.

A flow diagram indicating the operational use of the system is shown in Figure 6.

The first step in using the system is to define with relatively low accuracy the overall area of interest. This is done by specifying the distances in the x and y directions in nautical miles (nm) of the upper left corner of the area from the upper left corner of the frame, as well as the dimensions of the area in nautical miles. These coordinates are input to the first program which reads the MSS data tapes, joins the scan lines across 25 nm strips, and separates the MSS data by channel. The output tapes, one for each requested channel, contain only the data for the area of interest. Unnecessary

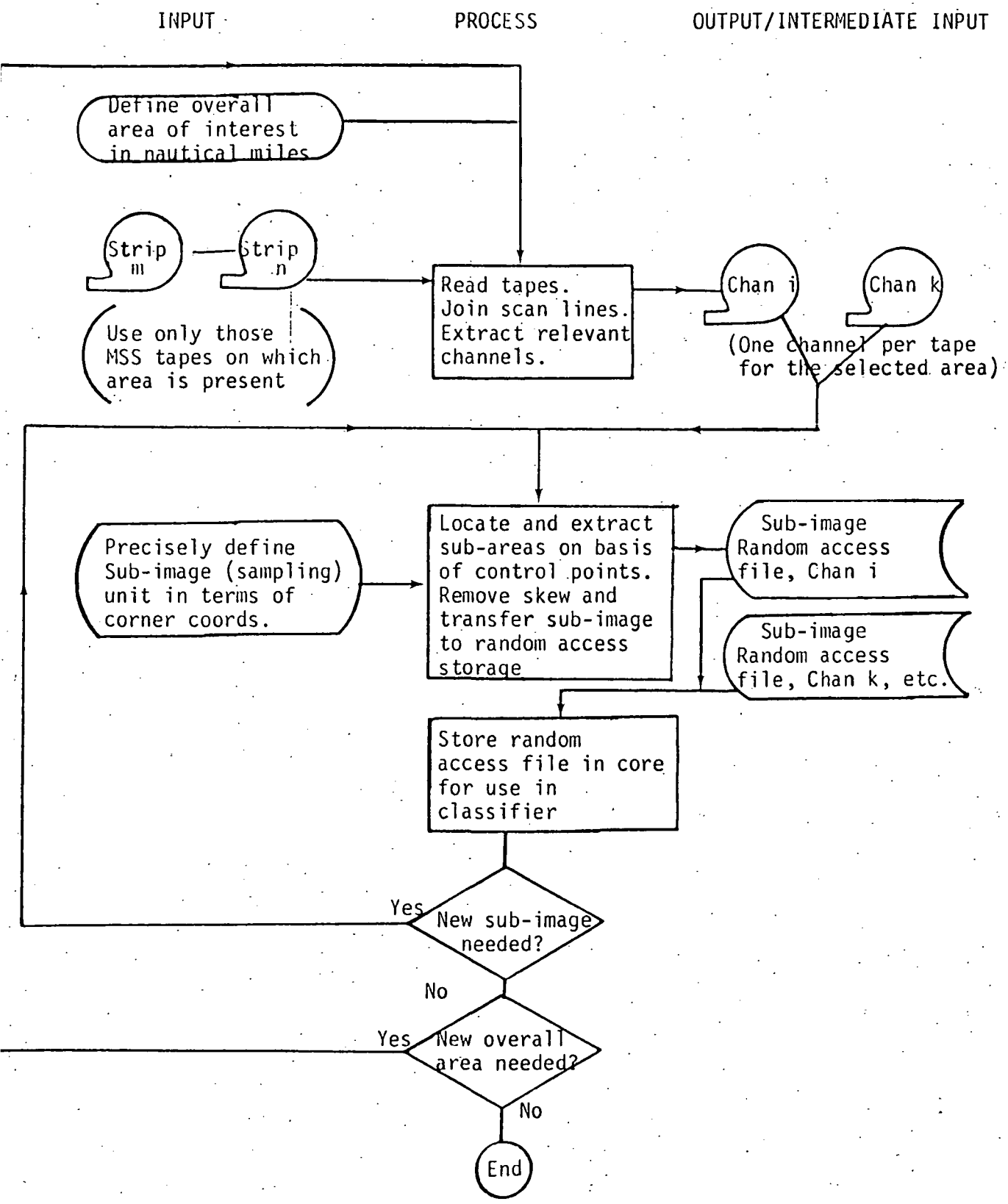


Figure 6. Flow Diagram for Image Handling System.

tape handling is avoided by only using those input tapes which contain MSS data for the area of interest, and by restricting the number of output tapes to the number of requested channels.

In a multistage forest survey, the first program would be used to select the forested area on the ERTS frame on which the inventory is to be made.

The second step extracts the sample unit areas from the general area. Considerable accuracy is required for this purpose, and, thus, the input for the second program consists of accurately specified corner coordinates for the sub-image. These coordinates are transformed to pixel locations, using skew and rotation parameters determined from a least-squares adjustment of the MSS data. The input for the least-squares adjustment are image coordinates and pixel locations of a set of corresponding points. The resulting RMSE of this adjustment is in the neighborhood of 2.0 pixels. The sub-image indicated by the transformed corner coordinates is extracted from the relevant channel tapes, corrected for skew, and then transferred to a random access storage device. This procedure is repeated for each channel.

The third step brings the image for the desired channel into core ready for use. An identification block is carried along with the image which specifies the position of its pixels in relation to those of its parent image as well as the channel number and other pertinent information.

Any image can be displayed on the line printer using a set of sixteen characters. Each one is uniquely related to a part of the spectral response range. Part of a printout of band 7 of frame E 1094-18224 is shown in Figure 7.

4.3.3 The Training System

This part of the system is used on a designated training area for which timber volume estimates are available. The training area should be representative of the rest of the terrain. The output of the system is a basic set of parameters needed for the timber volume estimation. As can be seen in the first part of Figure 8, the training system consists of six programs, some of which are also employed in the timber volume estimation process. We briefly discuss each of the programs and related techniques.

(a) The Feature Extraction Program. The image of the training area is blocked up in elements termed "intels." The system is particularly suited for work with 4x4 and 8x8 pixel intels. For each intel the feature extraction program extracts one tone and one contrast measure for each spectral band.

To compute these measures, we used the fast Walsh (Hadamard) transform algorithm in a computational form described by van Roessel (1972). The computation level used so far is the first level. That is, when using an 8x8 intel size we are working with the 4x4 grey value subtotals to compute the overall total as well as three contrasts.

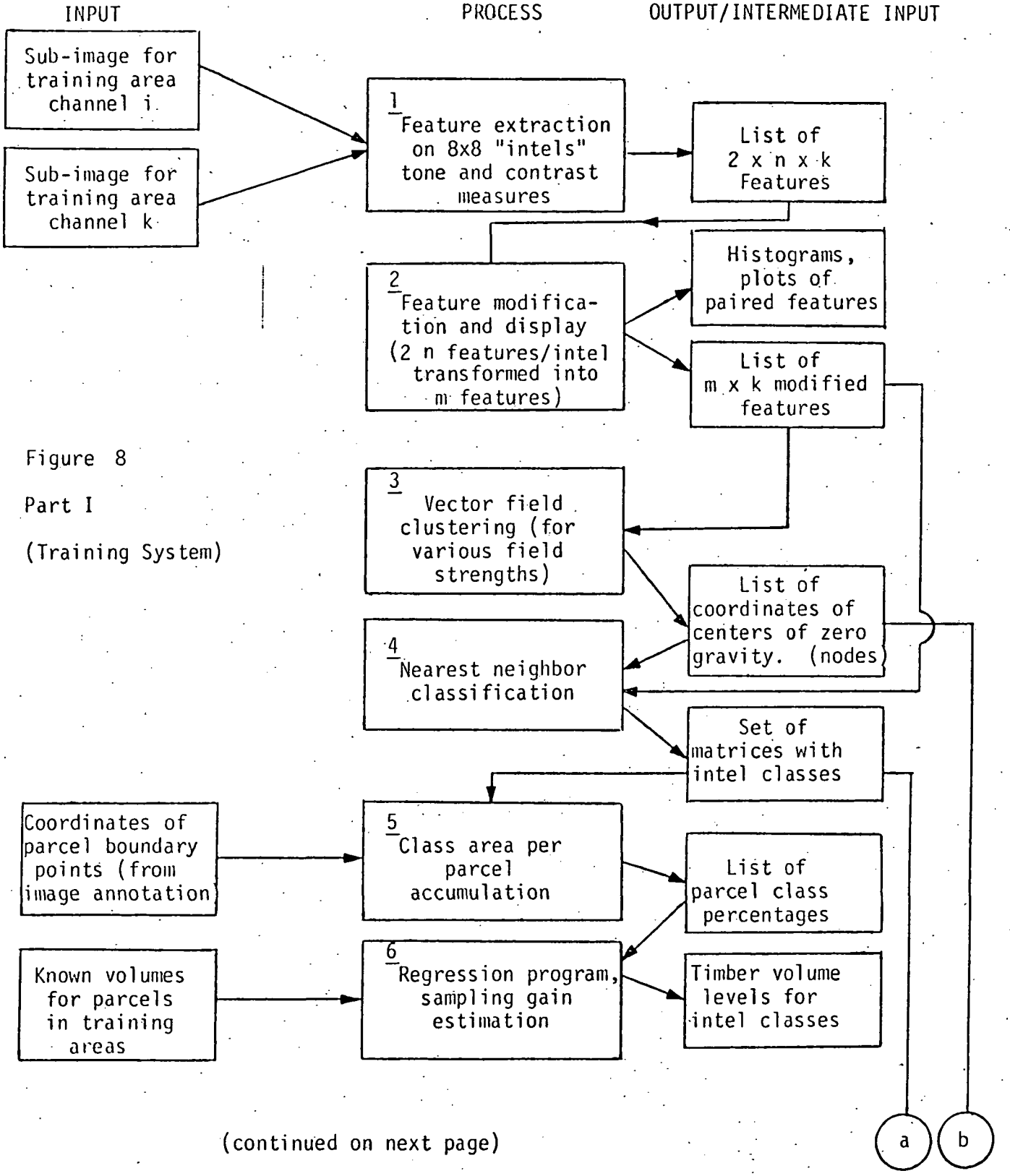


Figure 8

Part I

(Training System)

(continued on next page)

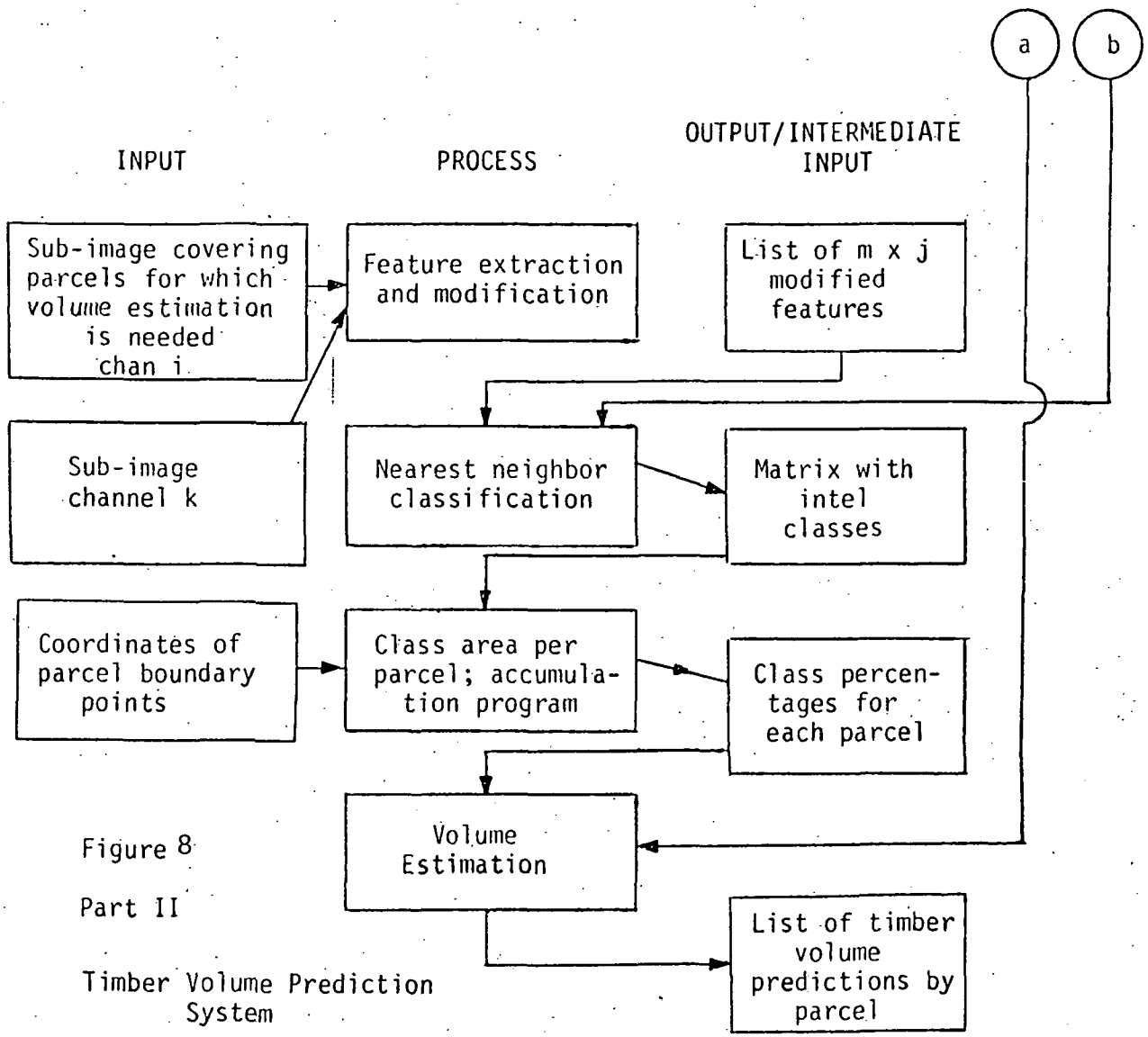


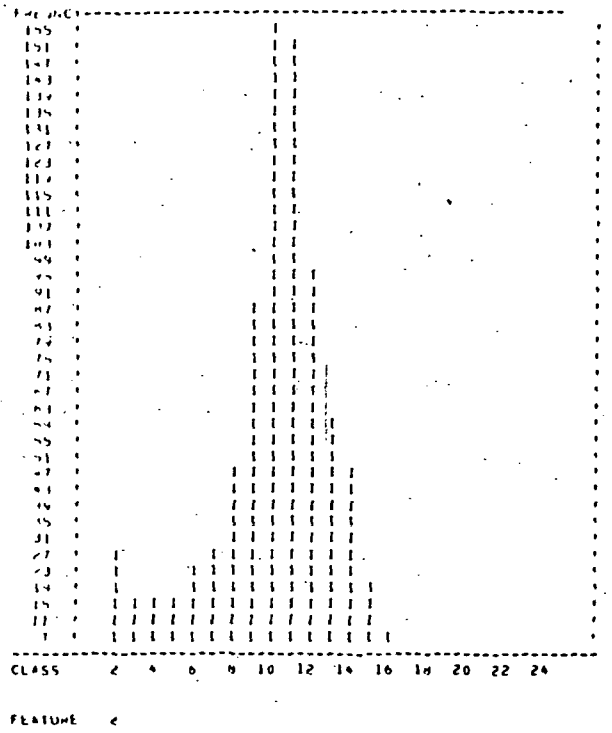
Figure 8. Flow Diagram of Digital Interpretation System

The overall total for the 8x8 intel is the tone value used. The square root of the sum of the three constrasts squared provides us with a rotation-independent contrast measure. To make this measure partially translation independent, the transform frame is moved around in a sub-image consisting of the intel plus a margin of one-fourth the intel size. The maximum contrast for all possible positions of the transform frame is the contrast used.

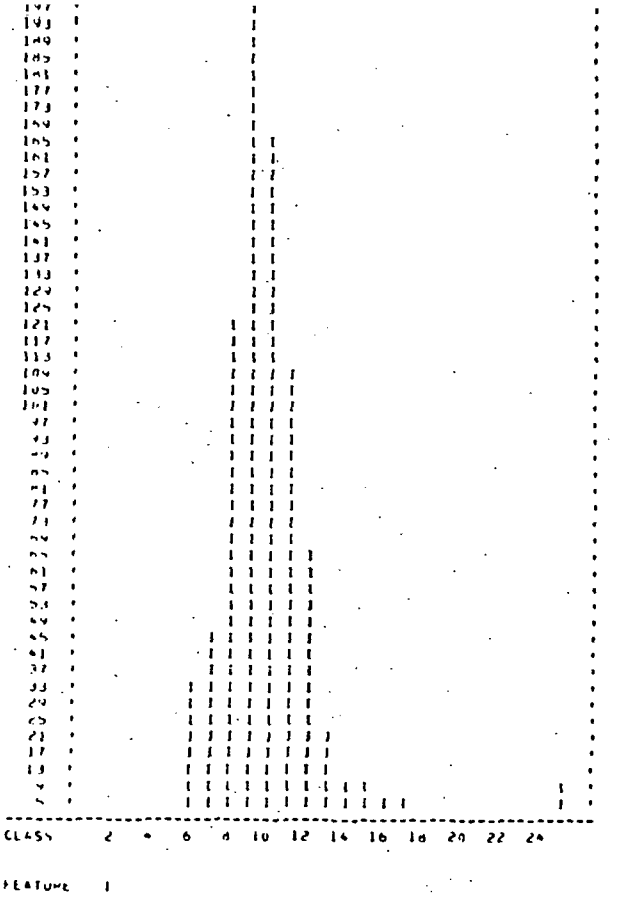
The final output of the program is a list of 2 x n x k features, where n is the number of channels used, and k is the number of intels in the area to be classified.

(b) The Feature Modification and Display Program. Feature extraction is followed by feature modification and display. Modifications may consist of taking combinations of tone values for various bands, such as the difference or the ratio. For this purpose one may write a short modification routine. Consequently, no restrictions are placed on the type or number of possible modifications.

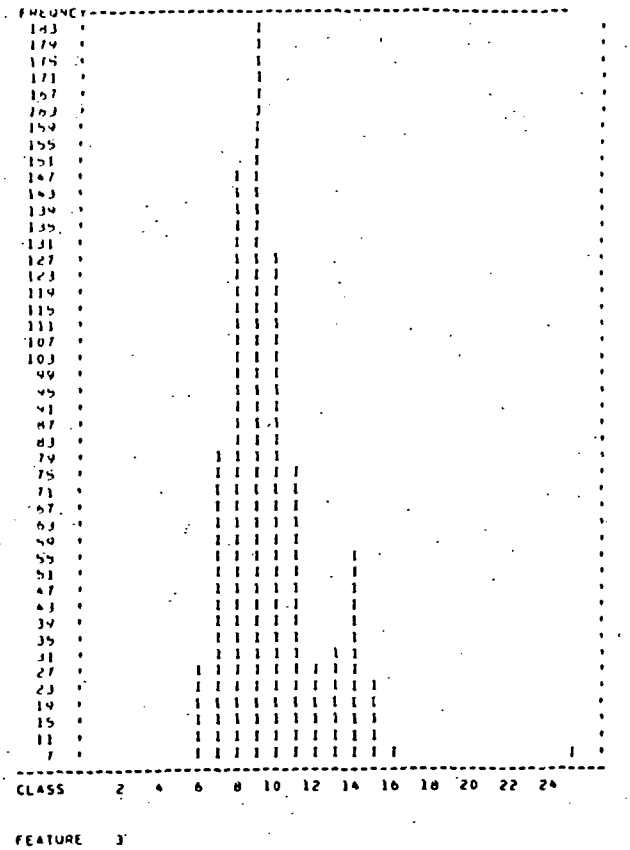
For each type of modified feature the program displays a histogram. Histogram examples for features compiled from the tone values of 816 8x8 intels for the sub-image covering our first test area are shown in Figure 9. The first two histograms are for bands 5 and 7, respectively; the third histogram shows the frequencies for the differences of the tone values of these bands. All tone values were standardized and transformed to a 0 to 30 range.



Band 7



Band 5



Band 5 - Band 7

Figure 9. Histograms for Standardized (0-30) Tone Values from 816 8x8 intels.

In addition to the histograms, two-dimensional plots are displayed for all combinations of modified features. An example of a plot of the tone values of band 5 (x-axis) versus the tone values of band 7 (y-axis) for the same 816 intels is shown in Figure 10.

The output consists of a list of modified features of dimension m x k, where m is the number of modified features per intel.

(c) The Clustering Program. The basic component of the unsupervised classification program is the data clustering routine.

Normally clustering routines are based on the assumption that the data will fall into clusters which are representative of multivariate normal distributions, with adequate separation zones between clusters. We anticipated that the difficult mountainous terrain with which we were working would yield data that would not adhere to these clustering conditions.

With this in mind, we selected G. A. Butler's (1968) vector field approach for the clustering algorithm. This method permits one's perspective of the data to range from locally sensitive (where each data point is a cluster) to globally sensitive (where the entire sample set is a cluster), by manipulating a single parameter, which we have named the field strength.

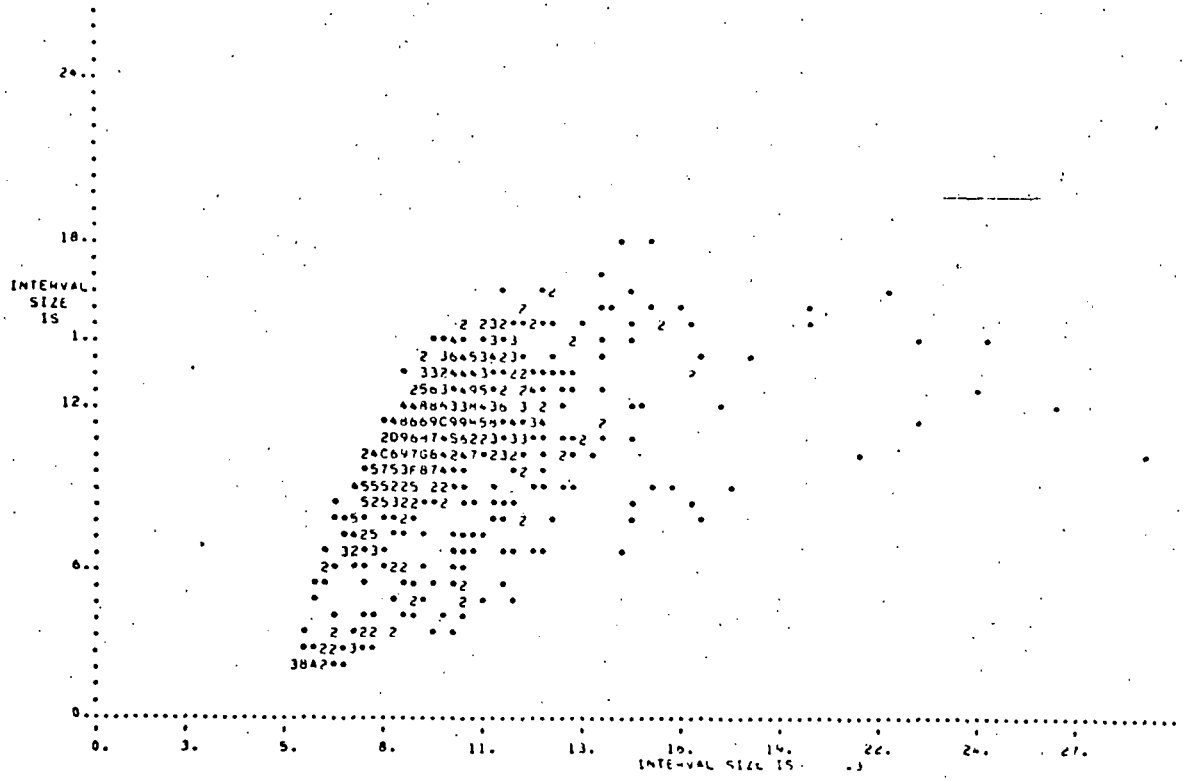


Figure 10. Plot of Tone Values (Standardized) of Band 5 versus Band 7 for 818 8x8 intels.

Basically, a gravitational field is generated in the n-dimensional sample space by using the simple Newtonian formula for an attractive force between two bodies, in which the squared distance has been replaced with a general power of the distance ($F = m_1 m_2 S^{-r}$, where S is the distance between two points with masses m_1 and m_2 and -r is the field strength). A gradient searching technique is then used to look for nodes or centers of zero gravity in the vector field. These nodes are representative of the cluster centers.

Several modifications to Butler's orginal technique were made. The major disadvantage was the large number of computations to be carried out. For each step in the sample space, the distance and force components from all other sample points must be computed. We partly eliminated this disadvantage by thinning the sample space with another clustering algorithm, the "chain" algorithm (Andrews, 1972). Rather than using a unit mass for all the sample points, we work with a reduced set of points with non-unit mass. The same chain algorithm is also used to define a small set of starting points, from which the gradient search for the zero gravity centers is started.

It was also desirable to include some kind of clustering stability evaluation as any desired degree of clustering can be obtained by varying the field strength. We arrived at a procedure whereby the field strength is reduced stepwise over a certain range, and the new starting points for each iteration

are the nodes from the previous iteration. The degree to which the old nodes resist being combined, while reducing the field strength, is a measure of the clustering stability. Typically, the field strength is varied from -3. to -2. with increments of 0.1.

(d) The Nearest Neighbor Classification Program.

After the cluster centers have been found, the intels can be classified according to the cluster with which they are associated. Roese (1969) has used a maximum likelihood procedure, on the assumption that his clusters resembled multivariate normal distributions. However, we are using simple non-parametric nearest-neighbor classification on the assumption that the data with which we are working are by no means normally distributed. The classification is based on the Euclidean distance between the point to be classified and the cluster centers. The point is assigned the class of the center to which it is closest. The n-dimensional space used is standardized by subtracting from each type of feature the overall mean and by dividing by the standard deviation for each axis.

The output of the program consists of a set of matrices (one for each field strength) indicating the class number for each intel.

(e) The Class Area Per Parcel Accumulation Program.

The next program uses the interpretation matrices to determine the area percentage of the total parcel area that is occupied by a given class.

From the interpretation matrices a classification image is generated by expanding the matrix in the form of 8x8 blocks of class numbers for each class number in the original matrices.

Land parcels, or aggregates of land parcels, are specified as input to the program. The pixel coordinates of the parcel corners are retrieved from a previously prepared list. The parcel boundary is then superimposed on the classification image, and the pixels of any given class that are within the boundary are tallied and divided by the total number of pixels in the parcel.

The class pixels within the parcel are counted using an "in or out" algorithm. Then a regression is performed in which the dependent variable is the known timber volume and the independent variables are the class percentages. This regression is based on the following model:

$$V_j - \bar{V} = B_1 P_{1j} + B_2 P_{2j} + \ldots + B_i P_{ij} + \varepsilon_j \qquad (4)$$

where V is the timber volume per square mile for parcel j; $\bar{V}$ is the average timber volume per square mile computed over all j parcels; p_{ij} is the class proportion of class i in parcel j; B_i represents the differential volume level for class i (in other words, if the parcel is all in this class we add B_i to $\bar{V}$); and ε_j is an error term.

Note that we subtract the average volume per square mile from the dependent variable, rather than estimate a constant term in the regression equation. The reason is that

the proportions sum to 1, so that the X matrix is not of full rank when a unit column is carried.

To evaluate the results we examine the following regression statistics: (1) the multiple correlation coefficient; (2) an F statistic for testing the hypothesis: $B_1 = B_2 = B_i = 0$, (in other words, the interpretation system provides statistically significant results); (3) t values for the individual betas, to test the significance of their difference from zero.

In addition, predicted timber volumes $\hat{V}_j$ are computed. These predicted volumes and the known volumes are then used to estimate the gain in efficiency that would result from the use of the predicted volumes in a variable probability sampling scheme. If we denote the variance for simple random sampling by V_{srs}, and the variance for variable probability sampling by V_{vps}, then the increase in precision is computed as follows:

$$\Delta G = \frac{V_{srs} - V_{vps}}{Vsrs} \times 100\% \qquad (5)$$

It can be shown that ΔG does not depend on the sample size.

4.3.4 The Timber Volume Prediction System

The major outputs of the training part of the digital interpretation system are the zero gravity center or node coordinates and the timber volume levels for the classes corresponding to the nodes. These outputs are the controlling parameters for the volume estimation system.

As is shown in the second part of Figure 7, the sub-image for which volume estimation is needed is the input to the feature extraction and modification program. The list of features is then entered into the nearest neighbor classifier where the intels are classified according to distances of the point to the centers of zero gravity. The resulting matrix with intel classes is then run through the class area per parcel accumulation program in which the class percentages in the relevant sampling units are accumulated. The percentages are entered into the volume estimation routine along with the volume levels from the training system. The result is a set of volume predictions for all the parcels that were contained in the sub-image from which the features were extracted.

The process is repeated for all relevant sub-images. The final list of volume predictions is used in the multistage inventory to determine the probability with which each unit will be selected for inclusion in the inventory sample.

5.0 SAMPLING EVALUATION OF MODELS AND TECHNIQUES

5.1 Introduction

Our objective in the evaluation of models and techniques developed during the investigation was to answer the following questions. (1) Is the developed model statistically significant?; will it supply significant information when applied to areas other than for which it was developed? (2) If the model is statistically significant, what will be the contribution of the model to the sampling efficiency when inserted in a sampling design? (3) What is the optimum sampling design for use with the model? (4) What are the basic parameters that make the technique or model optimally efficient?

In the following sections we will try to relate our findings resulting from the attempt to answer these vital questions.

5.2 Evaluation Methods

The usual procedure for evaluating a classification interpretation model is to obtain the model for the designated training area, and then to apply this model to a different test area. The "truth" is known for both the training and the test area, so that an evaluation can be made for both cases. Usually the success rate is considerably higher for the training area than for the test area.

Several methods may be used to evaluate a sampling estimator. One method is to estimate the variance of the estimator from a sample drawn from the actual population. In some cases where the

population can be simulated on a computer, a better evaluation method may be to let the computer sample the population, and then compute a variance for the estimator from a great number of samples.

A more difficult situation arises when the interpretation model of the first stage is coupled to the second stage through a sampling estimator. In this case one has to deal not only with the variation of the second-stage sampling distribution, but also with the variation inherent in the interpretive model. If the training site were a population belonging to a perfectly homogeneous super population of all possible training sites, the model variation would consist of (1) statistical variation around the model for a particular site; and (2) statistical variation of the model from site to site.

Under such circumstances one could probably evaluate the model sampling method estimator combination using simulation and Monte Carlo techniques. This approach may be justified for large-scale images of homogeneous forest types. In the present situation in which the effort is concentrated on small-scale images, a host of factors may influence the appearance of the terrain from site to site. Thus the super population of all possible training sites is very likely not statistically homogeneous, and so the only viable testing method seems to be the training-site/test-site approach.

In the following sections we first describe the estimators that were considered for the investigation. Then we indicate how the relative difference in variance for each estimator can be

determined. Finally, we show how the estimated difference or gain in precision should be interpreted differently for the training and the test areas.

5.2.1 Sampling Method Estimators

In our evaluation we considered the following set of sampling method estimators:

(1) Simple Random Sampling

$$\hat{y}_{srs} = \frac{N}{n} \sum_{i=1}^{n} y_i \qquad (6)$$

in which y_{srs} represents the estimate of the total timber volume for the population, N is the total number of units in the population, n is the number of units in the sample and y_i is the timber volume (estimate or true volume) associated with sample unit i.

(2) Ratio sampling

$$\hat{y}_{ratio} = \frac{y}{x} X \qquad (7)$$

in which x is the total of the timber volume estimates associated with the sample at stage 1; y is the total of the estimates (or true volumes) associated with the sample at stage 2, and X is the sum of the x's over the population.

(3) Regression sampling

$$\hat{y}_{regr} = y + b(X - x) \qquad (8)$$

in which b is a regression coefficient either computed from measurements made on the sample units at both stages, or obtained from such measurements from another sample taken from

the population. X represents the total of all estimates for the entire population at stage 1.

(4) Stratified sampling with proportional allocation

$$\hat{y}_{strat} = \sum_{h=1}^{L} N_h y_h \qquad (9)$$

In this case the population is stratified into L strata based on measurements obtained from the population at stage 1. Each stratum contains N_h units. The estimated mean timber volume for each stratum as obtained from samples at stage 2 is indicated by $\bar{y}_h$.

(5) Variable probability sampling

$$\hat{y}_{vps} = \frac{1}{n} \sum_{i=1}^{n} \frac{y_i}{p_i} \quad \text{where } p_i = \frac{x_i}{x} \qquad (10)$$

in which $\hat{y}_{vps}$ is the estimated total timber volume obtained with the variable probability sampling method. The variable probability p_i is the ratio of the estimate for that unit and the total of the estimates for the sample at the first stage.

5.2.2 Estimating the Gain in Precision for Each Sampling Method

In sampling terminology the term efficiency incorporates two components. These are the precision of the estimator and the cost associated with it. In our evaluation we assumed unit cost, so that sampling precision was our only criterion

for evaluating the performance of a model-estimator. In this case an increase in precision means a reduction in variance. Therefore, a logical method of comparing estimators is to compute the relative gain in precision when compared to simple random sample in as follows:

$$\Delta G = \frac{V_{srs} - V_{method}}{V_{srs}} \times 100\% \tag{11}$$

At times we will refer to $G = V_{srs} - V_{method}$, rather than to ΔG.

In the following we express G or ΔG for each of the estimators considered.

(1) Ratio estimates

$$\Delta G_{ratio} = \frac{2\rho(CV)_x(CV)_y - CV_x^2}{CV_y^2} \times 100\% \tag{12}$$

in which

ρ is the population correlation coefficient

CV_x is the coefficient of variation of X, and

CV_y is the coefficient of variation of Y.

(2) Regression Sampling

$$\Delta G_{regr} = \rho^2 \times 100\% \tag{13}$$

(3) Stratified sampling with proportional allocation

$$\Delta G_{strat} = \frac{\sum_{h=1}^{l} W_h \left(\bar{y}_h - \bar{y}\right)^2}{V_y^2} \times 100\% \tag{14}$$

(4) Variable Probability Sampling

The variance of the variable probability estimator can be written as follows:

$$V_{vps} = \frac{1}{n}\left(X \sum_{i=1}^{N} \frac{Y_i^2}{X_i} - Y^2\right) \tag{15}$$

Subtracting this variance from the one for simple random sampling we obtain

$$G = \frac{N}{n} \sum_{i=1}^{N} Y_i^2 \left(1 - \frac{X}{X_i}\right) \tag{16}$$

and the relative gain in the percentage mode is:

$$\Delta G_{vps} = \frac{G}{V_{srs}} \times 100\% \tag{17}$$

Noting that the gain formulas for the ratio estimators, and regression sampling were both dependent on the correlation coefficient, Zarkovic (1964) attempted to obtain an expression for (16) in terms of a correlation coefficient of variables related to x and y. To obtain this objective he used a binomial series of the type $(1+x)^{-1}=1-x+x^2$. When evaluating the gain in ratio and regression sampling, the minimum value of the population should be less than twice the population mean. Unfortunately, in the case of timber volume estimates this condition can easily be violated.

5.2.3 Gain Estimation In Relation to the Training-test Site Approach

Due to constraints in image processing and the availability of ground data, selected test and training sites could not be considered random samples from a population. Thus, we were not able to assume any functional distribution for the units comprising these sites. This is a disadvantage when considering the relative precision of a sampling design. A way out of such a situation was suggested by Cochran (1963), and used by Des Raj (1958) and Murthy (1967) in the comparison of estimators for different sampling methods. The solution is to regard the finite population as drawn at random from a super population which posesses certain properties. For the training/test site situation this solution takes on the following form:

(1) The training/test site combination can be considered as a finite population drawn from a finite super population of all possible training/test site combinations.

(2) The super population of all training/test site combinations can, in turn, be considered as a randomly drawn sample from an infinite super population with properties which are defined in the following.

In the previous sections we have denoted the second-stage population as y_i; i=1,.....,N. Certain attributes for each of these units can be measured at the first stage, say $a_{11}, a_{21},.....,a_{mi}$. The objective of the interpretation model

is to construct a predictor for Y_i which is a function of the attributes: $X_i = F(a)$. The properties to be assumed for the super populations are related to F(a) as follows.

(1) We assume that the predictor values are linearly related to the population unit values. For the training/test site combination we have:

$$Y_i = a + b\,X_i + e_i \tag{18}$$

where the properties of a, b, and e_i *with regard to* the super population of all possible training/test sites are assumed to be:

$$E(a) = \alpha,\ E(b) = \beta,\ E\left(e_i\right) = \varepsilon_i \tag{19}$$

$$Var(a) = V_a^2,\ Var(b) = V_b^2.\ Var\left(e_i\right) = V_{ei}^2 \tag{20}$$

(2) Thus, for the first super population we have

$$Y_i = \alpha + \beta X_i + \varepsilon_i \tag{21}$$

With regard to its super population, we assume the following properties:

$$E\left(\varepsilon_i/X_i\right) = 0,\ Var\left(\varepsilon_i/X_i\right) = \gamma X_i^g \tag{22}$$

These considerations are aimed at obtaining the expected value of the gain in precision of the different methods outlined in the previous sections. Because of the limited scope of the investigation we will present such a result for variable probability sampling only.

The gain in precision for variable probability sampling over simple random sampling can be expressed as in (16). To obtain the expected value of this expression we first must

obtain the expected value conditional on a given super population of training/test site combinations, and obtain the expected value of this expected value with respect to the second super population. This expectation is:

$$E(E(G/sp_1)) = \frac{N^2}{n}\left\{(\beta^2 + V_b^2)\ V_x^2 + \left(\alpha^2 + V_a^2\right) COV\left(\frac{1}{X_i}, X_i\right) + COV\left(\frac{V_{ei}^2 + \gamma X_i^g}{X_i}, X_i\right)\right\} \quad (23)$$

This expression allows us to make some conclusions regarding the basic difference between gain evaluation from the training site only, and gain evaluation from a combined training and test site.

When we evaluate the gain from a training site only, it serves as the test site at the same time and, hence, there is no super population of all possible training/test sites, as there is only one such combination. Thus, V_a^2, V_b^2, and V_{ei}^2 can be assumed to be zero in this case. The version of equation (23) for this instance is:

$$E\left(E\left(G/sp_1\right)\right) = \frac{N^2}{n}\left\{\beta^2 V_x + \alpha^2\left(1 - \frac{\bar{X}}{\bar{N}}\sum_{i=1}^{N}\frac{1}{X_i}\right) + \gamma COV\left(X_i^{g-1}, X_i\right)\right\} \quad (24)$$

An identical expression is found in Murthy, p. 189. It is the upper bound for (23). Thus, the results for a training/test

site evaluation are expected to be worse than those obtained from a training site only.

It can be obtained from (23) that variable probability sampling will be more efficient than simple random sampling if

$$\gamma COV\left(\frac{V_{ei}^2 + X_i^g}{X_i},\ X_i\right) > \left(\alpha^2 + V_a^2\right)\left(\frac{\bar{X}}{N}\sum_{i=1}^{N}\frac{1}{X_i} - 1\right) - \left(\beta^2 + V_b^2\right)V_x^2 \qquad (25)$$

It depends on the circumstances whether condition (25) is satisfied or not. In the training/test site situation it may not even be satisfied when the linear relationship goes through the origin ($\alpha = 0$), since the negative covariance term of $\left(\frac{1}{X_i}, X_i\right)$ will still be present because of V_a^2.

Only in the case in which the training site is used as the test site $\left(V_a^2 = 0,\ V_b^2 = 0,\ V_{ei}^2 = 0\right)$ and $g > 1$, do we have a situation in which variable probability sampling would always be superior to simple random sampling since:

$$\gamma COV\left(X_i^{g-1},\ X_i\right) > -\beta^2 V_x^2 \qquad (26)$$

which is satisfied since the left side of this expression is positive ($\gamma > 0$) and the right side is negative (see Murthy, p. 189).

The two important conclusions that can be drawn from the above analysis are: (1) the expected gain for an evaluation using a training site and a test site is necessarily less than the expected gain obtainable from a training site evaluation only; (2) the precision of simple random sampling is not the upper bound for the precision of variable probability sampling, since under certain conditions one can expect a negative gain in precision for the latter method, even when the regression line goes through the origin.

5.2.4 Evaluating the Statistical Significance of the Model.

One of the major questions that we attempted to answer was: is the developed model statistically significant in its application? This question is crucial. Since it would not make sense to evaluate the gain in precision obtainable with a certain model if the results of its application were entirely due to chance.

When working with the training sites we always performed a multiple regression. Most of this work concerned the model expressed in equation (4), section 4.3.3. The significance of this model lies in the significance of the independent variables which describe differential timber volume levels. For each level we inspected the t statistic associated with it. To assess the entire model we tested the null hypothesis (H_0: all differential timber volume levels are equal to zero) by computing

the F statistic:

$$F_{p-1;v} = \frac{SS(R/bo)/(p-1)}{s^2} \qquad (27)$$

where $SS(R/b_o)$ is the sum of squares attributable to the differential volume levels, s is the standard error of estimate obtained from the regression, p is the number of estimated levels + 1, and v=N-p. (Draper and Smith, p. 64).

For the test site we evaluated the model by performing a simple linear regression between the predicted values and the test values. An F statistic for the significance of this relationship was then computed.

The use of these F statistics was of major importance in testing the basic hypothesis underlying our research; namely, that useful information for forest inventory can indeed be obtained from high-flight and space photography.

5.3 Training Site Evaluation

The objective of the training site evaluation was two-fold: first, we wanted a preliminary evaluation of the technique and model, and secondly, after we obtained promising results, we wanted to optimize the parameters of the model. We present the results of these experiments later in this section. First, however, a description of the training sites is given.

5.3.1 The Training Areas

The 40 one-square-mile sections used to develop the U2 RC-10 interpretation model were described in Section 3.2. To train and evaluate the digital prediction system we used the following two sites.

The first site is a 64-square-mile portion of ERTS frame E 1094-18224 covering the northern part of California's Sacramento Valley and the Trinity Alps. It is situated in the vicinity of Trinity Dam, and covers a part of Clair Engle Lake, associated with this dam. The terrain is mountainous with elevations ranging from 2000 to 8000 ft.

The second area is also a 64-square-mile site imaged on frame E 1094-18222. It is further north, in the vicinity of the junction of Coffee Creek with the Trinity River. Elevations here range from 5000 to 7000 ft.

Both areas are contained in the Trinity National Forest, and are covered with timber stands consisting of a mixture of red and white fir, ponderosa pine and douglas fir.

The ownership pattern for both sites is of the checkerboard type. The individual land parcels are all approximately one square mile, alternately owned by the Southern Pacific Land Company and the Federal Government. Our ground truth in the test areas consists of volume data for some of the Southern Pacific land parcels.

One of the main reasons for selecting the two sites was that the first area contains a water body, whereas the second test area is all land.

The portion of ERTS frame E 1040-18222 covering the first area is shown in Figure 10. Band 5 is represented in Figure 11a, and band 7 is shown in Figure 11b. Note the accentuation of the underlying terrain form and water in the band 7 image, and the more detailed information (partly due to vegetation) in the band 5 image. The difference proved to play an important role in the digital interpretation.

5.3.2 Evaluation of the U2 Model

The U2 RC-10 interpretation model was described in Section 3.2. Multiple correlation coefficients for each of the models tested with color infrared and black-and-white photography for two interpreters are presented in Table 2.

For each of the model-image-type interpreter combinations we also calculated the gains in precision for the sampling methods described in Section 5.2.2.

The gains in precision for the selected model for two photo interpreters interpreting from color infrared photography are presented in Table 3.

Table 3. TRAINING AREA SAMPLING PRECISION GAINS FOR U2 MODEL

Sampling Method	Interpreter 1	Interpreter 2
	ΔG (percent)	
Ratio	55.1	42.0
Regression	55.1	42.0
Stratified	43.4	27.8
Variable Probability	49.9	40.3

This table confirms the difference between the two interpreters previously noted in Section 3.2. The results further indicate that a considerable gain could be obtained with the U2 model with all sampling methods. This result was not entirely substantiated when we applied the model to the test area, however. Variable probability sampling seems slightly inferior to ratio estimates and regression sampling. Stratified sampling seems inferior to variable probability sampling for this model.

5.3.3 Evaluation of the Digital Interpretation System

The training site evaluation for the digital interpretation system was cast into the form of a factorial experiment in which we systematically tried various combinations of bands and model parameters. The experiment was repeated for the two

training areas. The final system parameters and differential volume levels were then obtained by training the system on the two combined 64-square-mile areas.

In the following, we first outline the experimental design, then discuss the results of the experiment for each training area and finally present the results for the training run using the combined areas.

5.3.3.1 The Experimental Design

We described in Section 4.3.3 (Equation 4) how "known" timber volumes are regressed on the class area proportions for a set of parcels. This ground truth in the form of known volumes is essential for the training of the interpretation system. In the present case, however, not all land parcels had ground volume timber estimates. We therefore had to resort to photo interpretation for the interpolation of volumes between adjacent parcels with known volumes. This interpolation was performed on U2 RC-10 photographs by a highly trained photo interpreter with extensive ground experience in the areas. Ground volumes are known only for one-fourth of all parcels in the first test area. Half of the parcels of the second area have known timber volumes. We designated the mixture of known and interpreted volumes as "ground truth," keeping in mind how the volume figures were obtained.

At the same time, we developed the more objective interpretation model for the U2 photographs with other photo interpreters. They estimated a set of independent variables on the photographs rather than making a subjective volume estimate directly. This interpretation system is described in Section 3.2. Volume estimates obtained from these independent variables, as combined in a regression equation were obtained for both test areas. Hereafter, we refer to them as the U2 estimates.

The "ground truth" volumes and the U2 estimates were both used as the dependent variable in the regressions with the class area proportions for the 64 parcels. The purpose of using both types of estimates is that, in a multistage inventory, one would either have the option to directly correlate between the ERTS estimates and ground estimates (a two-stage survey) or to include another intermediate stage of aerial photography such as the U2 estimates (a three-stage survey). The hypothesis being tested is that a higher correlation is possible between ERTS and U2 estimates, than between ERTS and ground estimates, because of the closer resemblance of the resource between ERTS and U2 imagery than between ERTS imagery and ground observation.

The objectives of the experiment were to test different combinations of spectral bands and different

types of features extracted from the images. Specifically, we were interested in the following two hypotheses: (1) inclusion of a contrast feature increases the gain in precision; and (2) the inclusion of the difference between bands 5 and 7 increases the gain in precision. The latter hypothesis was of interest since various authors have recommended the ratio or the difference of these bands as being useful for biomass estimation (Vincent, 1973; Turner, 1973). To test these hypotheses, we designed an experiment of the factorial type in which we tested 16 different combinations of bands and features. Specifically, we experimented with the following factors: (1) factor a: band 5 present or absent; (2) factor b: band 7 present or absent; (3) factor c: the difference between bands 5 and 7 present or absent; (4) factor d: contrast measure for all bands or differences between bands used. Combinations of these factors resulted in the following "run" combinations listed in Table 4.

5.3.3.2 Evaluation of Experimental Outcome

First Training Area

For each of the run combinations listed in Table 4 digital interpretations were made. The results are presented in Table 5, where for each run combination

Table 4. "RUN" DESCRIPTIONS FOR FACTORIAL EXPERIMENT

Run Combination		Run Description
1.	(1)	Information for the best run combination applied at random in the regression program. Thus, results entirely due to chance
2.	a	Band 5 alone
3.	b	Band 7 alone
4.	ab	Bands 5 and 7
5.	c	The difference between bands 5 and 7
6.	ac	Band 5 and the difference between bands 5 and 7
7.	bc	Band 7 and the difference between bands 5 and 7
8.	abc	Bands 5 and 7 and the difference between bands 5 and 7
9.	d	Contrast measures for bands 5 and 7 alone
10.	ad	Band 5 and its contrast
11.	bd	Band 7 and its contrast
12.	abd	Bands 5 and 7 and their contrasts
13.	cd	The difference between bands 5 and 7 and the difference between contrasts for bands 5 and 7
14.	acd	Band 5, the difference between bands 5 and 7, and the difference between the contrasts for bands 5 and 7
16.	abcd	Bands 5 and 7, the difference between bands 5 and 7, and the difference between the contrasts for bands 5 and 7

are listed: (1) the multiple correlation coefficient (R); (2) the F statistic for the significance of the differential volume levels (F); (3) the upper 95% point of the appropriate F distribution; (4) the estimated gain from variable probability sampling; and (5) the number of volume levels estimated (NV). Results are listed both for the regressions with the "ground truth" and the U2 timber volume estimates.

Several interesting conclusions can be drawn from Table 5. Most important, an estimated gain in precision of over 50% is possible when using ERTS MSS data to define sampling probabilities at the first stage of a forest inventory sampling design. This is indicated by the ΔG values of 50.8% and 57.9% obtained for run abc. The corresponding F statistics (9.96 and 14.35) are highly significant at all probability levels (compare with 1.99). Thus, the hypothesis that the digital interpretation of ERTS MSS tapes can be used to increase the precision of sampling for timber volume is strongly confirmed.

Table 5. RESULTS OF ERTS MSS DIGITAL INTERPRETATION RUNS

TRAINING AREA 1

Run Comb.	"Ground Truth" R	F	F	ΔG_{vps}	NV	U2 Estimates R	F	F	ΔG_{vps}	NV
(1)	.32	1.49	1.99	8.5	10	.26	1.08	2.08	5.8	9
a	.32	2.33	2.17	9.5	7	.29	1.91	2.17	10.3	7
b	.40	11.74	2.76	15.4	3	.55	26.94	2.76	31.3	3
ab	.54	16.45	2.53	34.7	4	.67	14.30	2.14	49.3	8
c	.56	10.84	2.25	40.9	6	.67	19.78	2.25	52.5	6
ac	.62	9.02	2.04	44.9	9	.70	13.90	2.08	54.6	9
bc	.67	10.40	1.99	53.7	10	.68	17.48	2.17	53.7	7
abc	.66	9.96	1.99	50.8	10	.73	14.35	2.04	57.9	10
d	.56	8.01	2.00	32.5	8	.63	7.74	2.04	42.3	11
ad	.57	5.70	1.95	33.8	11	.62	7.30	2.04	41.8	11
bd	.46	4.72	2.10	19.9	8	.54	7.04	2.14	31.0	8
abd	.50	10.52	2.37	28.2	5	.55	13.13	2.37	32.8	5
cd	.57	5.13	1.92	41.3	12	.71	8.68	1.88	56.9	14
acd	.55	10.61	2.25	36.0	6	.62	15.21	2.25	42.9	6
bcd	.53	16.01	2.53	36.9	4	.68	35.44	2.53	52.9	4
abcd	.60	17.05	2.37	45.9	5	.70	29.34	2.37	55.1	5

In spite of these results, we wondered whether or not the significant results were due to the fact that this training area contained a water body. Water can be

detected quite easily on MSS band 7 and, in the test area, a zero timber volume is always associated with a water class. To evaluate this notion we examined 10 differential volume levels for the 10 classes of run abc and their corresponding t statistics at the 5% level of significance (two tailed test). The results are shown in Table 6.

Table 6. DIFFERENTIAL VOLUME LEVELS AND t STATISTICS FOR RUN abc (U2 Estimates)

Class #	Differential Volume Level (1000 bd.ft./ square mile)	t statistic (118 df)	Values of t (.05 significance level)
1	-2188	-2.83	-1.65
2	-2219	-.84	-1.65
3	-702	-.82	-1.65
4	274	.21	1.65
5	-203	-.08	-1.65
6	1662	2.03	1.65
7	3798	4.68	1.65
8	1439	1.22	1.65
9	381	.47	1.65
10	-3423	-7.09	-1.65

The most significant volume level in Table 6 is that of class ten. Inspection of the intel class matrix reveals that this class corresponds to the water body. Thus, wherever water occurs, the model subtracted 3,423,000 bd.ft. from the average timber volume level of 5,291,300 bd.ft. The difference is close to the standard error of estimate for the model. However, other classes, namely 1, 6 and 7, also are statistically significant, judging from their t values. For classes 6 and 7 the model added 1,662,000 and 3,798,000 bd.ft., respectively. These differential levels are certainly not due to water. Thus, we rejected the notion that all the explained variation was due to the presence of the water body.

We also analyzed the experiment in terms of the effects of the various factors and their interactions, making use of the 2^4 factorial design of the experiment. For the response variable we selected ΔG_{vps}. The computed effects are presented in Table 7.

Table 7. EFFECTS FOR DIGITAL INTERPRETATION EXPERIMENT

TRAINING AREA 1

(Response Variable ΔG_{vps})

Effect	"Ground Truth"	U2 Estimates
Mean	33.3	41.9
A	4.3	2.3
B	4.8	7.1
AB	4.0	4.3
C	21.0	22.7
AC	-3.1	-3.7
BC	1.3	-3.9
ABC	-2.2	-3.2
D	2.0	5.0
AD	-1.0	-4.9
BD	-7.9	-10.1
ABD	1.2	0.4
CD	-9.6	-7.8
ACD	1.7	0.4
BCD	4.6	11.1
ABCD	4.0	-0.3

The mean for the regressions with the U2 estimates is about 9% larger than the mean for the regression with the "ground truth" volumes. This difference tends to confirm the hypothesis that the ERTS digital interpretation results correlate better with other imagery interpretation data than with direct ground truth. However, we had ground volume estimates for only one-fourth of all parcels. The other parcels had interpolated volumes only. Thus another possibility would be that the interpolation technique was not as good as the multivariate interpretation model that was used to obtain the U2 estimated ground volumes.

The second conclusion that can be drawn from the effects of Table 7 is that the difference between bands 5 and 7 (C effect) dramatically influences the gain in precision with an additive effect of approximately 22%. This confirms the hypothesis that the difference between bands 5 and 7 is extremely useful for the purpose of biomass estimation.

The third conclusion that can be made is that the effect of the inclusion of contrast is positive, but otherwise small. It is therefore probable that the use of a contrast measure would not pay in an operational mode under similar terrain and environmental conditions evaluated at the same time of year.

Second Training Area

To conclusively establish the fact that a significant gain could also be obtained with the system in the absence of a water body, we also performed a similar experiment in a land-only second training area.

We omitted the contrast factor in this experiment as it was of little significance in the first training area. Therefore, the design was a 2^3 factorial design rather than a 2^4 one.

The "ground truth" for this test area was again a mixture of Southern Pacific Land Company data and U2 interpretations. A set of pure U2 estimates was also used for the evaluation as in the first experiment.

The experimental outcomes for the run combinations 1-8 of Table 4 are presented in Table 8.

Table 8. RESULTS OF ERTS MSS DIGITAL TRAINING RUN

TRAINING AREA 2

Run Comb	"Ground Truth" R	F	$F_{(.95)}$	G_{vps}	NV	U2 Estimates R	F	$F_{(.95)}$	G_{vps}	NV
(1)	.32	1.49	2.04	8.5	10	.26	1.08	2.08	5.8	9
a	.44	3.60	2.37	17.9	5	.51	5.08	2.37	27.0	5
b	.25	.96	2.37	5.0	5	.32	1.63	2.37	9.4	5
ab	.60	3.88	2.04	25.1	9	.69	6.10	2.04	40.7	9
c	.56	5.33	2.25	27.5	6	.62	7.22	2.25	40.4	6
ac	.63	3.52	1.95	30.1	11	.65	3.92	2.04	40.1	10
bc	.63	3.21	1.92	32.2	12	.68	4.10	1.92	40.9	12
abc	.60	3.88	2.04	25.1	9	.69	6.10	2.04	40.7	9

A comparison of the results in Table 5 and Table 8 show that the overall gain decreased by about 10% for the second training area. The corresponding F statistics also decreased but they are still significant at the 0.05 level in most cases (compare F with $F_{(.95)}$). An interesting exception is the run combination b, for which band 7 was used only. Since band 7 is most suitable for the detection of water bodies, and the first training area did have a water body, the logical conclusion is that the significance of this band (used by itself) in the first experiment is due to water. Band 7 used in conjunction with band 5, however, still plays an important roll. Either band 5 can be used on one axis, and band 7 on the other, or the difference can be used. To compare these two modes of combining the two bands, we computed the experimental effects for the gain in variable probability sampling as we had done for the first experiment. The values of these effects are presented in Table 9.

Table 9. EFFECTS FOR DIGITAL INTERPRETATION EXPERIMENT

TRAINING AREA 2

(Response Variable ΔG_{vps})

Effect	"Ground Truth"	U2 Estimates
Mean	21.4	30.6
A	6.3	13.0
B	0.9	4.6
AB	0.3	2.6
C	14.6	19.8
AC	-8.5	-13.3
BC	-1.0	-4.1
ABC	-5.1	-2.5

Comparing the C effect (the difference between bands 5 and 7) with the AB effect (bands 5 and 7 on separate axes) we can indeed conclude that taking the difference between the two bands causes the largest increase in gain. This result then confirms the earlier results for the first training area, where the difference effect was also the largest single effect. Next to the difference between bands, band 5 seems to make the largest single contribution. However, when using band 5 on one

axis and the difference between 5 and 7 on another we do not obtain the sum of the effects due to each of these factors separately, as we can see from the negative AC interaction.

This second experiment also confirmed the result that better correlations can be obtained between ERTS estimates and the U2 estimates than with the mixture of U2 estimates and ground truth. The mean effects were about 10% lower than in the first experiment probably due to the absence of water.

5.3.3.3 Training of the Digital System Using the Combined Training Areas

Noting that the best results in the first experiment were obtained with run abc, and that this run yielded very good results in the second experiment also, we decided to use this combination to train the system on the combined training areas. The use of band 5, 7 and their difference also appealed because all factors would be utilized.

Features were extracted for both training areas. The feature lists were combined and jointly submitted to the clustering and nearest neighbor classification program. The resulting intel matrix was separated according to

study area, and the class percentage per parcel program was run for each area. The results were combined again and the final regression involving all 128-square-mile parcels was performed.

We selected a clustering with seven classes for the final result from a larger set of clusterings. Four of these classes seemed highly significant. Volume levels and t statistics for each of these classes, as well as their significance probability, are presented in Table 10.

We also used the U2 estimates for the combined training. The reason was that these estimates were more consistent than the "ground truth," which, for a large part, was made up of U2 estimates in the first place.

Table 10. VOLUME LEVELS AND t STATISTICS

(FINAL TRAINING)

Class	Volume Level (1000 bd.ft./ square mile)	Differential Volume Level (1000 bd.ft./ square mile)	t	Significance Probability
1	11501	6489	4.02	>0.9995
2	8297	3234	5.19	>0.9995
3	6028	1015	0.93	<0.90
4	4467	-545	-0.78	<0.90
5	4373	-638	-0.47	<0.75
6	3454	-1557	-2.12	>0.975
7	1592	-3420	-5.91	>0.9995

In this table are presented the volume levels as well as the differential volumes levels. As can be seen, the range of volume levels is very much representative of the actual volume range, although in reality occasionally a parcel with more than 11 million bd.ft. will occur. The consensus among photo interpreters working on this project, and also our opinion, is that these high volumes cannot be detected on high-flight or space photography. At the low end of the scale, class 7 does not seem to represent a land class entirely void of timber volume. We verified that this class represents mostly water and bare land. However, some instances were noted where the system confused the dark tone of water with the dark tone of heavily vegetated south facing slopes. The residual volume may well be due to this type of confusion.

The volume levels of classes 3, 4 and 5 have differential volume levels with t statistics which are not significant at the 0.05 level. This is due to the fact that the levels for these classes are very close to the mean, so that the t value is necessarily small. Thus classes 3, 4 and 5 are mostly representative of the mean volume level which, of course, has the highest significance of any volume level.

The F statistic for testing the hypothesis that all differential levels are equal to zero was 15.44. At the .995 significance level this value compares with $F_{7,128} = 3.09$; thus the hypothesis can safely be rejected. Moreover, the obtained F value satisfies a criterion mentioned by Draper and Smith (P. 64) that, to obtain a useful prediction tool, the F value should be larger than four times the nominal value at the selected percentage point (15.44 > 12.36).

Estimated gains in precision for the combined training areas are presented in Table 11.

Table 11. GAINS IN PRECISION FOR COMBINED TRAINING AREAS

Method	Relative Gain (Percentage)
Ratio	43.4
Stratified	26.7
Regression	43.4
Variable Probability	43.9

The gains obtained were about the average of the gains obtained for each training area separately. With the exception of stratified sampling, the sampling methods uniformly indicate a gain of 43%.

With these results in hand, it seemed that all necessary prerequisites for a successful application of the system over a much larger area were present. The results of such an application are presented in the following section.

5.4 Test Site Evaluation in a Sampling Survey Context

5.4.1 Introduction

To obtain a realistic appraisal of an interpretation system, it is necessary to evaluate the system on a test site that is either not related or far more extensive than the original training site. Therefore, we tested the U2 high-flight interpretation model and the MSS digital interpretation system on units obtained from an area of approximately 1500 square miles; whereas the training site of the digital system consisted only of two blocks totalling 128 square miles.

In accordance with a primary objective of this investigation, we tested the interpretive models in a sample survey context. Our objectives were: (1) to determine whether the models that were statistically significant for the training sites were also significant when applied to the larger test sites; (2) to establish the gain in sampling precision under test site conditions, and (3) to investigate the decline in gain from training to test site. Secondary objectives were: (1) to gain insight about optimum stage combinations by determining

which models correlated best from stage to stage; (2) to examine the sampling methods exhibiting the highest gains when used with relatively weak interpretive models in a test site situation.

5.4.2 Sampling Design Considerations

5.4.2.1 Types of Sample Units

We worked with two types of sample units; (1) parcels consisting of one-square-mile GLO land sections, and sample units consisting of blocks of adjacent parcels approximately four miles on a side.

At an early stage in our ERTS research, when the geometric accuracy and resolution of the ERTS MSS images were uncertain, we considered using sample units of multiple land sections. After performing the resections described in Section 2.5, however, we concluded that it would be feasible to annotate individual sections and fractions thereof. Parcels are logical information units for timber management in many areas of the United States since they define land ownership and are, therefore, useful sample units.

Sample units consisting of blocks of adjacent parcels were used in the Southern Pacific timber inventory. The reason for using this type of primary sampling unit

was that each block was covered by one 1:40,000 scale aerial photograph. Hence aerial photographs could be selected at random. Up to eight parcels may be included in this type of primary sample unit.

In subsequent discussions we refer to the parcel sample unit as the SP parcel, and to the primary sample unit as used by Earth Satellite Corporation in the Southern Pacific timber inventory as the ES PSU or PSU.

5.4.2.2 Stage Combinations

The following types of timber volume estimates for the SP parcels were available to us for use in the final analysis:

(1) Digital estimates obtained from the ERTS MSS tapes.

(2) High-flight volume estimates obtained with the U2 model.

(3) Volume estimates obtained from a detailed interpretation of 1:40,000 scale aerial photographs, as well as other relevant auxiliary information.

(4) SP parcel records consisting of estimates obtained from a variety of sources.

For the ES PSUs we had obtained the following types of timber estimates:

(1) Digital estimates obtained from the ERTS MSS tapes.

(2) High-flight volume estimates obtained with the U2 model.

(3) Volume estimates obtained by subsampling the ES PSUs with 70 mm photography and on the ground, using multistage variable probability sampling.

(4) Volume estimates obtained from SP parcels records.

With these estimates at our disposal we were able to consider the stage combinations indicated in Table 12 where the four types of estimates described above are designated as MSS, U2, ES and SP, respectively.

Table 12. STAGE COMBINATIONS USED IN FINAL EVALUATION

		Parcels first stage		ES PSU's first stage	
		MSS	U2	MSS	U2
	MSS	-	-	-	-
second	U2	x	-	x	-
stage	ES	x	x	x	x
	SP	x	x	x	x

5.4.3 Final Interpretation Work

For our final analysis, a total of 43 PSUs was selected. Each PSU was examined on the U2 photographs to ensure that no logging had taken place since the Southern Pacific inventory in 1971. A total of 138 parcels were contained in the 43 PSUs. These parcels were used in the final parcel analysis.

Digital Interpretation

Our digitial interpretation system performs on rectangular image blocks. To minimize computer time, we grouped the PSUs into six subgroups. Each subgroup was completely contained within a portion of an ERTS MSS image called a sub-image. To provide the programs with the capacity to handle sub-images of sufficient size for multiple channels, we modified our programs to utilize the Univac 1108 FH432 high-speed drum. With this device not more than one image strip with a horizontal dimension equal to the sub-image width and a vertical dimension of 12 pixels needs to be stored in core at any one time for each band used.

We used our image handling system to extract the sub-images of bands 5 and 7 for the six areas. These sub-images were the input to the feature extraction and nearest neighbour classification program. The classification results were fed into the class percentage per parcel accumulation program, which at the same time calculates the timber volume predictions from the previously established timber volume levels. This last program called on a file with parcel corner coordinates of all the parcels contained in the set of PSUs. Timber volume predictions were listed according to the parcel designation of township, range and section.

U2 Interpretation

A smaller subset of the PSUs was also annotated on the U2 photographs. Not all PSUs could be interpreted from these

photographs because the coverage was limited to two flight lines. In all, 30 PSUs were interpreted consisting of a total of 95 parcels. In our subsequent analysis we refer to this set of parcels as the U2 set, whereas we will designate the entire set of 138 parcels as the full set.

1:40,000 Scale Estimates

A requirement of the Southern Pacific Inventory was that a timber volume estimate be provided for each parcel. To satisfy this requirement Earth Satellite Corporation developed a combination of an interpretation system and prediction model, for use with 1:40,000 scale black-and-white aerial photographs, that yields timber volume predictions by tree diameter class and species for each parcel.

In this system, individual parcels are annotated on the aerial photographs by means of a precision resectioning method. They are then interpreted for homogeneous breakdowns of tree size, density, and distribution in the forest cover. The delineations that are made in this manner are termed forest systems. An interpretation code is recorded for each system. Ground samples are taken and timber volumes are recorded for the sample of forest systems. A multiple regression analysis is then performed, in which the dependent Y variable is the recorded ground volumes by diameter class, and the independent X variables are the density of the crown cover as recorded in the forest system code. Other variables such as site class

and the previously recorded parcel volume are also included. The regression results are used to predict the timber volume for each forest system in a parcel. Accumulation of the system predictions provides the parcel total. This prediction is then adjusted such that the total for all parcels corresponds to estimates obtained with the multistage survey.

Considering all other types of estimates, the 1:40,000 scale figures were the best volume estimates available for the final analysis of this investigation. Not only were they most up-to-date, but they also resulted from a judicious combination of interpretation results, existing information, and a careful adjustment to reflect the latest inventory totals.

SP Parcel Records

Parcels records kept by the Southern Pacific Land Company provided us with timber volume estimates obtained from several sources. Mainly, these figures were the result of earlier timber cruises and photogrammetric inventories, with adjustments made following sale preparations and timber sales.

The parcel records were used as one input to the 1:40,000 scale timber estimation system. They are considered to be less accurate and more outdated than the results of the new system described above. However, when we started our final analysis the results of the 1:40,000 scale interpretation were not yet available, so that the SP parcel records provided the

best data to work with in the beginning. Later on, we incorporated the 1:40,000 scale estimates into this investigation.

EarthSat PSU Estimates

To obtain the PSU estimates for the various sampling stages we simply totalled the individual parcel estimates for each PSU. However, for the ES PSU estimates we used the volume estimates obtained by subsampling the ES PSUs with 70 mm photography and ground dendrometry. The sampling design used for this work was the multistage variable probability design, making the estimates unbiased and consistent.

5.4.4 Final Evaluation Procedures

As mentioned in Section 5.4.1, two of the main objectives of the final evaluation were to determine the significance of the image interpretation models and the gain in sampling precision obtainable by introducing the results from these models into the sample design. However, in a sampling survey context, where for reasons of practicality the sample units cannot be of equal size, the use of an interpretation model is not the only means to reduce the sample variance. The land area covered by forest is also important. Thus, determining the combined effect of area and the estimates from the interpretation model on the gain in sampling precision became a secondary objective of our evaluation.

The total sampling unit timber volume estimate is simply the product of the volume per unit of area and total area. However, the gain attributable to the product is not simply the product of the gains due to each factor. As a matter of fact, to derive a statistical relationship for the gain due to the product in terms of the gain of the components for the various sampling methods considered is non-trivial. Instead, we used the following procedures:

(1) Interpretation Models Alone: We calculated the mean volume per square mile from the unit total and then performed our analysis on the mean volume figures, removing the area effect to some degree.

(2) Area Alone: We used one set of predictions which were purely a function of area and a mean volume of 5 million board feet per square mile.

(3) Interpretation Model And Area Combined: For the combined effect, we used the sample unit totals.

In our final analysis program we evaluated the stage combinations indicated in Table 13 for each of the three procedures outlined above for the two types of sample units (parcels and PSUs).

For each of these combinations we evaluated the gains in precision associated with the sampling methods discussed in Section 5.2.1. To assess the statistical significance of the linear relationship between the estimates of the two stages, we

Table 13. TEST RESULTS FOR THE MSS DIGITAL INTERPRETATION SYSTEM
SAMPLE UNIT: SP PARCEL

Stage Combinations	Ratio	Relative gain in precison (percent)			Statistical Significance		
		Strat.	Regr.	Var. Prob.	F	$F_{0.95}$	r
TOTAL VOLUME							
Full Set							
MSS-ES	32.8	32.5	33.9	34.3	70.0	3.90	0.58
MSS-SP	31.8	25.3	27.9	32.3	52.6	3.90	0.53
U2 set							
MSS-U2	45.7	47.0	35.8	38.2	51.9	3.96	0.60
MSS-ES	21.7	28.0	25.4	24.2	31.8	3.96	0.50
MSS-SP	24.9	20.8	23.4	26.2	28.5	3.96	0.48
MEAN VOLUME							
Full set							
MSS-ES	9.4	18.8	13.3	5.6	20.9	3.90	0.36
MSS-SP	15.2	13.0	13.7	13.2	21.6	3.90	0.37
U2 set							
MSS-U2	18.3	30.3	17.7	13.0	20.0	3.96	0.42
MSS-ES	-2.4	17.8	6.8	4.2	6.8	3.96	0.26
MSS-SP	11.1	12.0	11.0	11.0	11.5	3.96	--
AREA ONLY							
Full Set							
Area-ES	22.9	14.3	27.2	29.5	50.8	3.90	0.52
U2 set							
Area-ES	16.7	11.7	23.1	24.2	31.1	3.96	0.50

MSS: MSS digital interpretation system estimates.
US : High-flights U2 model interpretation estimates.
ES : EarthSat estimates obtained by combining interpretation of 1:40,000 scale aerial photographs with SP parcel records.
SP: Estimates obtained from SP parcel records.
Ratio = ratio estimate; Strat. = stratified sampling (proportional allocation).
Regr. = regression sampling, Var. Prob. = variable probability sampling.

performed the usual linear regression analysis of variance in which the significance of the relationship can be tested with the F statistic. This statistic is the ratio of the Mean Sum of Squares due to regression and the Mean Sum of Squares due to error (see Section 5.2.3).

5.4.5 Results of the Final Evaluation

This section describes the results of our final evaluation. The first part covers the results obtained with the digital MSS interpretation system; the second part covers the U2 high-flight interpretation model. Each of the parts is subdivided according to the sample units used: the parcel and the ES PSU. For each of these subsections the results are tabled by (1) stage combination (2) the type of estimates used; (3) the total, the mean, area only; and (4) by the data set used.

5.4.5.1 MSS Digital Interpretation Results

Sample Unit SP Parcel

The test site interpretation results for the MSS digital interpretation system and the parcel sample unit are presented in Table 13. Without having resorted to any further statistical analysis, we are of the opinion that the results of this table support the following conclusions.

(1) The F statistics listed in Table 13 show that all linear relationships are significant at the 95% probability level (compare F with $F_{0.95}$). All of the relationships, with the exception of the MSS-ES and MSS-SP combinations of the U2 set for the mean volume are also significant at the 0.999 level. Thus, there is no doubt regarding the statistical significance of the applied results of the models. The remaining question is: What benefits can be obtained from their application?

(2) We already mentioned that land area plays an important role in the magnitude of the variance. To eliminate the area effect, so as to assess the pure effect of the interpretation model, we used the procedures outlined in the previous section. The analysis of the mean volume per square mile shows that the contribution of the digital system, when averaged over stage combinations, data sets and sampling methods, amounts to about 13%. The disadvantage of using the mean volume is that additional variation is introduced in the process of converting from the total volume to the mean volume per square mile. Hence, the 13% estimate may be on the low side.

Comparing the area only gains with the total volume gains we can compute the differences listed in Table 14, which are attributable to the digital interpretation system.

Table 14. RELATIVE GAIN DIFFERENCES ATTRIBUTABLE TO THE DIGITAL INTERPRETATION SYSTEM (computed from Table 13)

Stage Combinations	Ratio	Strat.	Regr.	Var. Prob.
Full Set				
MSS-ES	9.9	18.2	6.7	6.8
U2 Set				
MSS-ES	5.0	16.3	2.3	0.0

With the exception of stratified sampling, these differences are generally much smaller than the 13% gains for the mean volume per square mile indicated in Table 13. For variable probability sampling it would seem that no gain was realized from the interpretation model.

Another way to evaluate the sampling methods is to express the contribution of the interpretation model in terms of the loss in precision that would be incurred if area only were used, rather than when combined with the

volume prediction. In this manner, the percentage is based on a value which does not depend on the variation of the size of the sample units. Table 15 presents these losses for the stage combinations used in Table 14.

Table 15. RELATIVE LOSSES TO BE INCURRED WHEN USING THE AREA ONLY ESTIMATE, RATHER THAN THE PARCEL TOTAL

Stage Combinations	Ratio	Relative Loss (Percent)		
		Strat.	Regr.	Var. Prob.
Full Set				
MSS-ES	14.8	27.0	10.3	7.35
U2 Set				
MSS-ES	6.4	22.7	3.1	0.0

(3) We stated earlier (section 5.3.3.3) that the U2 estimates were used to train the digital interpretation system. Therefore, one would expect better results for the MSS-U2 stage combination than for the MSS-ES and MSS-SP stage combinations. An inspection of Table 13 reveals that this is indeed the case. When averaging over the sampling methods, the relative gain for the MSS-U2 combination for mean volume amounts to 19.8%, versus 11.3% for the MSS-SP combination.

(4) During the course of the investigation, we discovered that high timber volumes per acre escape detection on small-scale images. The logical reason for this phenomenon is that the main characteristics interpreted from the image that are related to volume are spatial. On the other hand, timber volume is only partly a function of the spatial arrangement of the trees. It is therefore, logical to hypothesize that image estimates are better correlated with other image estimates than with estimates partly based on ground data. This notion was confirmed in the digital interpretation experiment where we obtained consistently better results with the U2 estimates than with the SP parcel record data.

When inspecting the difference between the MSS-ES and MSS-SP stage combinations for mean volume, it would seem that the MSS-ES combination has lower relative gains than the MSS-SP combination, where the MSS-ES combination is one in which photo estimates in the first two stages are related. For total volume, the difference seems to be reversed in the cases of regression sampling and stratified sampling.

(5) In Table 13 the results are presented for the full set and the U2 set. Here, it can be seen that, generally, the results for the full set are better than those for the U2 set. Two PSUs not included in the U2 set are situated in training area B. Therefore when using the U2 set, this part of the training area is excluded from the analysis, which may explain the decline in gain for the U2 set.

(6) An important aspect of our final evaluation was to assess the performance of the sampling methods when coupled with an auxiliary interpretation model. For this evaluation two parameters were of major interest; (1) the overall yield of the method in terms of gain in sampling precision, and (2) the stability of this yield for different stage and interpretation model combinations. To assist in this evaluation we ranked the sampling methods, based on the gains shown in the columns of Table 13. These rankings are the following:

	Yield	Stability
1.	Stratified	Regression
2.	Regression	Stratified
3.	Variable Probability	Variable Probability
4.	Ratio	Ratio

Thus it would seem that for the particular situation and type of data involved, stratified and regression sampling would be preferable over variable probability sampling and ratio sampling, although in many cases the differences between these methods may be slight. However, all methods yield a higher precision than straight multistage sampling that fails to utilize data obtained from space and/or aerial platforms.

Sample Unit: ES-PSU

The results for the MSS digital interpretation system for the ES-PSU sample unit are listed in Table 16. We did not make an area only analysis for this type of sample unit. However, in addition to the MSS-ES combination (with the ES estimates obtained by subsampling with 70 mm photography and tree dendrometry) we have listed the gains for the SP-ES stage combination. This combination was used in EarthSat's Southern Pacific Land Company timber inventory, in which the ES-PSUs were selected on the basis of existing SP parcel record data. Table 16 indicates that a gain of 56.6% was obtained in this inventory by using the existing estimates in variable probability sampling. If the results of the MSS digital interpretation system had been used instead, the gain would have been 44.2%

Table 16. TEST RESULTS FOR THE MSS DIGITAL INTERPRETATION SYSTEM
SAMPLE UNIT: ES PSU

Stage Combinations	Relative gain in precision (percent)				Statistical Significance		
	Ratio	Strat.	Regr.	Var. Prob.	F	$F_{0.95}$	r
TOTAL VOLUME							
MSS-ES	43.1	-	49.0	44.2	37.5	4.08	0.70
SP-ES	49.7	-	61.8	56.6	63.2	4.08	0.78
MEA VOLUME							
MSS-ES	9.9	6.4	11.3	17.0	4.98	4.08	0.34
SP-ES	39.6	67.8	51.6	48.3	41.6	4.08	0.72

MSS: MSS digital interpretation estimates.
ES: EarthSat estimates obtained by subsampling with 70 mm photography and tree dendrometry.
SP: Estimates obtained from SP parcel records.

Insofar as applicable, the conclusions that can be drawn from Table 16 do not contradict the results of Table 13. All linear relationships are again significant at the 95% level. For total volume the best results were obtained with regression sampling (stratified sampling was not considered). The contribution due to the interpretation system as determined from the mean volume analysis averaged over the sampling methods was 11.2%. Variable probability sampling gave the highest result of 17% for this analysis.

5.4.5.2 U2 RC-10 Human Interpretation Model Results

Final test results for the U2 model are presented in Table 17 for the SP parcel sample unit, and in Table 18 for the ES-PSU sample unit. The results in these tables can be summarized as follows:

(1) All relationships, except one, are statistically significant at the 0.95 level. The exception is the mean volume relationship for the U2/ES stage combination.

(2) The mean volume results, which indicate the contribution of the model proper, averaged over stage combination, sample units and sampling methods, indicate an average gain of approximately 11%. Surprisingly, this gain is in the same category as the one obtained with the MSS

digital interpretation system. When inspecting the gain figures for the various sampling methods and stage combinations, however, one notices that the U2 model exhibits much greater variation from method to method. Stratified sampling for the U2/ES stage combination, using the parcel as the sample unit, yields a gain of more than 40%. In this situation, regression sampling would have yielded a gain of 26%. Variable probability sampling would have contributed nothing under these circumstances. If the SP parcel records had been used, a 20% loss in precision would have been incurred in this case.

One can speculate that the greater variability of the U2 model among data sets, stage combinations and sample units is due to non-linearity of the model. The large gains obtainable with stratified sampling support this notion. The non-linearity may result from the interpreters changing their standards over time. A digital system is not subject to such changes.

(3) The notion that image-related estimates correlate better with other image-related estimates than with ground related data is supported by the

results in Table 17. Gains are generally higher for the U2/ES combination than for the U2/SP combination.

(4) Again ranking the sampling methods according to their mean and variance when computed over the columns of Tables 17 and 18, we obtained the following rankings for yield and stability.

Yield	Stability
Stratified	Stratified
Regression	Ratio
Ratio	Regression
Variable Probability	Variable Probability

5.4.6 General Conclusions Regarding the Final Test Site Evaluation

Considering all of the factors that were involved in the final evaluation, we believe that the results obtained support the following conclusions with regard to each factor:

(1) The combined effect of area and interpretation model is not simply the product of the components; instead there seems to be a negative interaction.

(2) The overall gain obtainable for the MSS interpretation system and the U2 model (averaging over sample units and sampling methods) seems to be in the same category, namely, 13%. However, the variation between methods and units is much greater for the U2 model. With

Table 17. TEST RESULTS FOR THE U2 RC-10 HUMAN INTERPRETATION MODEL
SAMPLE UNIT: SP PARCEL

Stage Combinations	Relative gain in precision (percent)				Statistical Significance		
	Ratio	Strat.	Regr.	Var. Prob.	F	$F_{0.95}$	r
TOTAL VOLUME							
U2/ES	19.6	43.0	37.3	24.8	55.5	4.08	0.61
U2/SP	13.7	31.9	23.3	4.4	28.4	4.08	0.48
MEAN VOLUME							
U2/ES	7.8	40.4	26.1	0.5	32.8	4.08	0.51
U2/SP	0.9	27.2	12.6	-20.2	13.4	4.08	0.36

U2: High-flight U2 interpretation model estimates.
ES: EarthSat estimates obtained by combining interpretation of 1:40,000 scale aerial photographs with SP parcel records.
SP: Estimates obtained from SP parcel records.

Table 18: TEST RESULTS FOR THE U2 RC-10 HUMAN INTERPRETATION MODEL
SAMPLE UNIT: ES PSU

Stage Combinations	Relative gain in precision (percent)				Statistical Significance		
	Ratio	Strat.	Regr.	Var. Prob.	F	$F_{0.95}$	r
TOTAL VOLUME							
US/ES	7.2	-	33.8	8.2	14.29	4.08	0.58
MEAN VOLUME							
US/ES	-7.5	26.8	8.5	0.6	2.61	4.08	0.29

U2: High-flight U2 interpretation model estimates.
ES: Estimates obtained by subsampling ES PSUs with 70 mm photography and tree dendrometry.

this model a maximum gain of 40.4% is indicated in the mean volume analysis using stratified sampling. The largest gain for the digital ERTS system is 30.3%, also for stratified sampling in the MSS U2 stage combination. On the other hand, the smallest gain obtained for the U2 model is -20.2% for variable probability sampling in the U2 SP stage combination; the smallest gain for the digital system is -2.4% for ratio sampling in the MSS ES stage combination and U2 data set.

(3) The type of sample unit does not seem to change the contribution of the digital interpretation model in any significant way: a different set of EarthSat data used for the ES-PSU confirmed the magnitude of contribution of 13%.

(4) The results for the full data set were better than those obtained with the partial U2 set; the difference may be explained by the fact that practically none of the PSUs in the U2 set are situated in the system training area.

(5) Considering the behavior of the various sampling methods for the combined digital and U2 models in terms of their yield and stability, we obtained the following ranking:

Yield	Stability
Stratified	Regression
Regression	Stratified
Variable Probability	Ratio
Ratio	Variable Probability

from which it appears that under the prevailing circumstances stratified and regression sampling are to be perferred to ratio and variable probability sampling. However, there were certain situations in which variable probability sampling was best.

6.0 SUMMARY, RECOMMENDATIONS AND CONCLUSIONS

6.1 Objective of the Investigation

The investigation was concerned with a multistage forest inventory system. Its main objective was to evaluate the usefulness of ERTS-1 imagery for the space platform stage of the inventory. Secondary objectives were the development and testing of new techniques to make optimum use of available remote sensing information, not only at the space level, but also at the subsequent aircraft levels.

Within this framework we outlined three areas of interest: (1) the development of precision annotation techniques for the types of imagery involved; (2) the development of interpretation models and systems for the various image types; and (3) the testing of these models in a realistic survey context for different sampling methods, stage combinations and sampling units.

6.2 Work Performed

To achieve our objectives, we designated a test site in the Trinity Alps of Northern California where we had conducted a timber inventory for the Southern Pacific Land Company. As a result of this inventory, we had at our disposal a large volume of pertinent data that could be used to conduct our experiment. Southern Pacific Land Company ownership is of the checkerboard type, where as the basic is unit the one-square-mile GLO land section. A great deal of our work was centered around this type of land unit.

The ERTS coverage used for our research was obtained in October of 1972. During that same period a U2 under-flight was made during

which color infrared photographs were taken with an RC-10 camera. Our work started with the development of an analytical precision sample unit annotation technique for the U2 photographs. We used a method similar to the one we had used in the Southern Pacific timber inventory on 1:40,000 scale photographs. However, the control for each photo was not obtained from maps, but from the results of a block adjustment of the U2 photographs. The RMSE of this block adjustment was approximately 10 m, an excellent result for 1:120,000 scale photographs. Using the technique, all relevant SP parcels were annotated on the U2 photographs.

The next phase was to develop an annotation process for the ERTS MSS images. Here, we recognized the special problems resulting from the scanner geometry and the space platform. To cope with these problems we developed a special flexible resection technique in which any parameter can be enforced at a preset value. In this manner we were able to introduce ephemeris data to improve the accuracy of the resection. The MSS resections showed that the accuracy with which map points could be located on the MSS imagery was in the range of 100 to 200 meters RMSE. The SP parcel boundary coordinates were digitized from 10 USGS 15' quadrangle maps and then projected onto the MSS images using the resection results.

After the completion of the image annotation we focused our attention on the development of interpretation models and techniques. Specifically we developed a human interpretation model to estimate timber volumes from the U2 photographs, and we programmed a digital

system to provide timber volume estimates from the MSS computer tapes.

The digital ERTS MSS interpretation system was designed in the form of three components: (1) an MSS image handling system; (2) a training system; and (3) a biomass or timber volume prediction system. The image handling system was required to handle the portions of the image corresponding to the sample units. It interacts with the precision annotation process to provide precise digital results for parcels with irregular shapes in diverse locations. The training system consists mainly of an unsupervised clustering routine. This routine is based on Bulter's vector field method in which cluster centers are equated with zerogravity nodes. The classes associated with the cluster center are related to the image by means of a nearest neighbor classification method. For each class we estimated the timber volume level by regressing known parcel volumes on the class percentages for each parcel. The prediction system uses the cluster centers and the class volume levels to predict timber volume by parcel using nearest neighbour classification and regression methods. The combined result of the systems components is a continuous volume prediction capability by parcel.

The last part of our work was to test the models and techniques in a sample survey context. The models were evaluated in both the training and the test phases. For the case of variable probability sampling, we were able to show that the evaluation in the training

phase is an upper bound to the results for the test phase. Therefore, a decline in results when switching from training to test site seems unavoidable. The same is true, for the other sampling methods, but was not demonstrated in this investigation.

The objective of the final evaluation was to assess the models over a much larger area. We were particularly interested in (1) the difference in results between the training site and the test site; (2) combinations of estimates provided by the models as they would be combined in a multistage survey; (3) sampling methods to be used for these stage combinations; and (4) the performance of the interpretation models with different types of sample units.

6.3 Results Obtained

The results of our resection experiments showed that the MSS geometry would allow the use of the Southern Pacific Land Company parcel (one square mile or even less) as the basic annotation and sample unit.

A representative cross section of these units was used to obtain the coefficients for the U2 human interpretation model. The results of this regression analysis (training) supported the idea that a good linear relationship could be developed between the model estimates and the estimates obtained from SP records. Multiple correlation coefficients of 0.7 and higher were obtained.

The digital interpretation system was first tested on two 64-square-mile contiguous training areas, one of which contained a

water body. In all our tests, we evaluated the reduction in variance or gain in precision that could be obtained by using the auxiliary information provided by the interpretation model with the following sampling methods: ratio estimates, stratified sampling, regression sampling and variable probability sampling. The first test area supported the idea that relatively high gains in precision could be obtained using the digital interpretation technique. Gains in the order of 50% were not uncommon.

Using this test area we performed a factorial experiment in which we systematically tried various band combinations, with and without the inclusion of a contrast factor. A major result of this test was the discovery that most of the response of the system was due to the inclusion of the difference between band 5 and band 7 in the clustering space. Contrast was not found to be a significant factor.

To establish the fact that the good results were not entirely due to the presence of a water body in the first test area, we repeated the experiment on a second test area which contained no water. The results of the first experiment were entirely confirmed by this test. Indicated gains in sampling precision were somewhat lower, however: approximately 30%.

A combined training was performed using the first and second training areas. Results for this run were in the order of a 40% gain in sampling precision.

To test the digital interpretation system and the U2 model in the context of a multistage inventory, we applied the models to a much larger test area. This was not a contiguous area but it consisted of a conglomerate of sample units distributed over a 1500 square mile site. Two types of sample units were used: the SP parcel and the ES-PSU which was made up of from 1 to 8 adjacent parcels.

The objectives of this test site evaluation were (1) to evaluate the models; (2) to investigate the decline in gain from training area to test area; (3) to investigate different stage combinations; (4) to investigate the behavior of the models relative to the two types of sample units; and (5) to evaluate the various sampling methods.

A major result of this final evaluation was that with very few exceptions all linear relationships tested were statistically significant.

The gain in precision, however, had seriously declined and was now in the order of 10 to 20%. To evaluate this gain in terms of the pure contribution of the interpretation model, we had to eliminate the effect of area by converting timber volume estimates for the total parcel to estimates on a mean volume per square mile basis. This conversion may have introduced some additional variation. When estimates based on area only were tried, it appeared that the additional gain achieved for the parcel <u>total</u> estimates was not the product of the gains for the area only and mean volume estimates. Instead, there appeared to be a negative interaction.

Testing of the U2 human interpretation model revealed that the gains in sampling precision for this model were on the average not much better than those for the digital interpretation system. This was surprising, since the training results had been superior to those obtained for the digital system. However, The variation in gains relative to the various combinations of sampling methods, stage combinations and sample units was much larger for the U2 model than for the digital system. For the U2 model a maximum gain of 40.4% was achieved for one combination, a minimum of -20.2% for another. The extremes for the digital system were 30.3% and -2.4%.

Additional conclusions that can be drawn from the results obtained in the final evaluation are the following. The type of sample unit did not seem to make any difference in terms of the gain in sampling precision provided by the models. Experimentation with stage combinations revealed that the digital estimates correlated best with the U2 estimates. This was no doubt due to the fact that the U2 estimates were used to train the digital system. In a more general sense it seemed that photo estimates were better correlated with other photo estimates in comparison with ground derived estimates. An analysis of the sampling methods involved showed that regression sampling and stratified sampling are preferable to ratio estimates and variable probability sampling under the circumstances. In particular, the use of variable probability sampling is not advisable when correlations are low and the linear assumption may not hold.

This is also true for regression and ratio sampling, but use of the latter two may be less risky in unknown situations.

6.4 Recommendations And Conclusions

Recommendations for a continued research effort fall into two categories: (1) those related to improving the present models and techniques for use under the conditions presented in this report; and (2) those related to a much broader application of ERTS MSS imagery and U2 high-flight imagery in multistage forest inventories on a larger scale under a variety of conditions.

Some recommendations of the first category are the following. In our opinion, the digital interpretation system can be greatly improved on. The tests described in this report are only the first tests realized with the system. Two areas for improvement come to mind immediately. The intel size of 8x8 pixels is probably too large, and system performance could probably be enhanced by switching to a 4x4 or a 2x2 intel size. The storage problems associated with this intel size were solved already in the later stage of this investigation.

In our work with the MSS digital data we also noticed that the distinction between water and dark north facing slopes with high volumes was a precarious one. The decline in gain experienced from training to test area may partly be due to a subtle shift between these tone signatures. Additional research would be necessary to remedy this situation. Perhaps we were handicapped in this respect by the fact that we used October imagery with a relatively low sun angle.

The U2 human interpretation model could be improved and stabilized over larger areas by using more than one photo interpreter. Several interpreters could mutually verify their interpretation standards as the interpretation progresses. Individual interpretations could then be averaged to provide more consistent estimates.

Perhaps one of the most important questions of multistage forest inventory has not been dealt with in this research. We investigated the interpretation models in terms of two stage combinations. However we did not attempt to define optimal combinations of several models, sampling methods, and multiple stages simultaneously. When considering multistage inventory, one should be concerned with multiple combinations of interpretation models and sampling methods, as the hidden benefits of the technique would result from these optimum combinations. Time and budgetary constraints prevented us from exploring this area, however.

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